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ABSTRACT

Currency carry trade returns are on average large and non-normally distributed. While the literature has found different explanations for the existence of carry trade returns, the higher order moments of their return distribution still pose a puzzle. We propose a new model to explain these non-normal properties of currency carry trade returns, by assuming that agents are loss averse and overweight states with low probabilities. This combination of loss aversion and probability weighting is called crash-o-phobia. Using non-linear least squares and risk-neutral state prices implied by currency options, we estimate this crash-o-phobia model to price developed and emerging market currencies. The parameter estimates reveal crash-o-phobic beliefs and preferences with significant differences across currencies. Compared to a model with rational beliefs and CRRA utility, our crash-o-phobia model performs significantly better at explaining the whole distribution of currency carry trade returns.

Keywords: currency carry trade returns, loss aversion, belief estimation, probability distortion, crash-o-phobia

JEL Classification: G11; G12; G40

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I. Introduction

According to the uncovered interest parity (UIP) the expected return from investments in different currencies with different levels of local interest rates should be zero. However, the UIP does not hold empirically which is known as the forward premium puzzle and has led to the famous currency carry trade investment strategy.[1] That is, borrowing in low interest currencies and lending in high interest currencies consistently generates positive excess returns. These high average returns are usually negatively skewed and exhibit fat tails.[2]

While traditional risk based factor models such as the CAPM or the Fama-French factors struggle to explain currency carry trade returns (Burnside (2012)), currency specific risk factors such as HML, dollar risk or FX volatility can explain the average level of carry trade returns (Lustig, Roussanov, and Verdelhan (2011), Verdelhan (2018), Menkhoff, Sarno, Schmeling, and Schrimpf (2012)).[3] However, these risk factors fail to capture higher order moments of carry trade returns. In this regards, recent studies have identified two types of risks for which carry trade investors are compensated for. Currency carry trade returns display high downside market risk (Dobrynskaya (2014), Atanasov and Nitschka (2014)) and high crash risk or the presence of rare disasters such as peso problems (Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015), Farhi and Gabaix (2015), Jurek (2014), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011)). Similarly, we aim at explaining the whole distribution of carry trade returns. Instead of creating a new risk factor or exogenously modelling crash risk, we explicitly model investor preferences to capture these non-normal properties.

To show that a model with crash-o-phobia can explain carry trade returns, we first, specify the investor's utility function and belief formation process and then, we estimate the model parameters by fitting past currency returns to state prices derived from option data.[4] Motivated by cumulative prospect theory (Tversky and Kahneman (1992)), we propose a new asset pricing model including loss aversion and probability weighting. We refer to this combination of loss

[1]The failure of the UIP is first documented by Tryon (1979), Hansen and Hodrick (1980) and Fama (1984). Comprehensive literature surveys about exchange rates and the forward premium puzzle can be found in Froot and Thaler (1990), Lewis (1995) and Engel (1996, 2014).

[2]See for example summary statistics of currency carry trade returns documented by Burnside, Eichenbaum, and Rebelo (2011), Dobrynskaya (2014) or Jurek (2014).

[3]HML refers to the high-minus-low risk factor which goes long high interest rate currency and shorts currencies with low interest rates.

[4]Estimating model parameters by fitting the model to option-implied data is a common approach in the pricing kernel literature. (See for example Bliss and Panigirtzoglou (2004) and Hens and Reichlin (2013).)

aversion and overweighting states with low probabilities as *crash-o-phobia*. To estimate the crash-o-phobia Euler equation we fit risk-neutral state prices derived from currency options to past carry trade returns for different developed and emerging market currencies. Empirically, we find that carry trade investors exhibit substantial loss aversion and overweight states with low probabilities. We compare our crash-o-phobia model to the standard expected utility model with CRRA preferences and rational beliefs. The results show that loss aversion, belief estimation and probability weighting significantly improve the fit relative to the benchmark model.

In the cross-section, we find that the parameters estimates of developed market currencies depict higher loss aversion and less overweighting of tail probabilities. In line with the literature (Ranaldo and Söderlind (2010)), the Swiss franc (CHF) and the Japanese yen (JPY) are identified as safe haven currencies. In contrast, the parameter estimates of emerging market currencies reveal that investors buying high interest rate currencies are less loss averse but strongly overweight events with small probabilities, such as the possibility of a severe crash and a subsequent devaluation of the foreign currency. Overall, our findings on the crash-o-phobic behavior of currency investors are consistent with the literature showing that downside market risk and crash risk are priced in currency markets. In particular, we show that our parameter estimates for loss aversion and probability weighting can explain the skewness and excess kurtosis of currency carry trade returns, both in the time-series as well as in the cross-section of currency returns.

The literature on downside market risk as an explanation for currency carry trade returns is consistent with the model of loss aversion by Tversky and Kahneman (1992). They postulate that investors are more averse to losses than they are enticed by gains. Based on the economic rationale of investors' loss aversion, Dobrynskaya (2014), Lettau, Maggiori, and Weber (2014) and Atanasov and Nitschka (2014) find that downside market risk is priced in currency returns.[5] Dobrynskaya (2014) identifies a global downside risk market factor, which loads positively on high interest currencies, and finds that currency carry trades perform disproportionally worse in times of stock market crashes. Similarly, Lettau, Maggiori, and Weber (2014) propose a downside risk CAPM where both the market price of risk and the beta of currencies with the market are allowed to vary conditional on the aggregate stock market return. While these two studies investigate forward discount sorted currency portfolio returns, Atanasov and Nitschka (2014) find that global

[5]Downside risk measures the covariance of an asset's return with the market in the worst states of the world, i.e. when the overall market performs poorly. It is also a relevant risk source for returns of other asset classes, see for example Ang, Chen, and Xing (2006), Botshekan, Kraeussl, and Lucas (2012) or Galsband (2012).

downside risk is also priced in bilateral currency excess returns. Overall, high interest currencies tend to depreciate during aggregate market downturns and hence, returns to currency carry trades seem to be a fair compensation for their high downside market risk.

Besides this positive exposure to equity market downside risk, currency carry trade returns are also exposed to systematic crash risk induced by rapid devaluations of high interest currencies. Brunnermeier, Nagel, and Pedersen (2008) argue that these sudden exchange rate moves, which are unrelated to fundamental news, are due to the unwinding of carry trades when speculators near funding constraints.[6] Alternatively, Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) show that the high currency carry trade returns reflect a peso event risk which comes in the form of a high value of the stochastic discount factor (SDF) rather than large carry trade losses.[7] Jurek (2014) uses out-of-the money foreign exchange options and computes returns to a crash-hedged carry trade strategy. He finds that the high returns to currency carry trades cannot fully be explained by a peso problem, since the crash risk premia only accounts for one third of carry trade returns. In a similar vein, Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015), Farhi and Gabaix (2015) and Chernov, Graveline, and Zviadadze (2018) develop theoretical models to formally evaluate the crash risk of different currencies and find that approximately one third of carry trade returns is due to disaster risk. Moreover, Dupuy (2015) constructs an empirical global tail risk factor, where tail risk is understood as the interaction of different moments, and shows that it prices the cross-section of currency carry trade returns.

To summarize, the literature shows that investments in high interest currencies deliver large positive returns, which are negatively skewed, exhibit fat tails and crash occasionally due to some rare event or systematically along with the stock market. The aim of this paper is not to provide a new risk factor as an explanation of currency carry trade returns,[8] but to rationalize these stylized properties using a crash-o-phobia approach. The crash-o-phobia approach includes loss

[6]Brunnermeier and Pedersen (2009) develop a formal model to explain liquidity spirals. They show that negative skewness of investment assets is partly due to the amplification of negative shocks when speculators hit their funding constraints and unwind their positions. On the other hand, Abreu and Brunnermeier (2003) argue that when investors hold on to their carry trade positions too long, because they do not know when others unwind their positions, then, a currency crash after a bubble can even be price correcting.

[7]The peso problem was first mentioned by Rietz (1988) and refers to the effects on inference caused by low-probability events that do not occur in the sample.

[8]Besides downside risk and crash risk, the literature has proposed many other risk factors which try to explain the cross-section of currency carry trade returns. Examples are the HML carry factor (Lustig, Roussanov, and Verdelhan (2011)), the Dollar factor (Verdelhan (2018)), global currency volatility (Menkhoff, Sarno, Schmeling, and Schrimpf (2012)), FX correlation risk factor (Mueller, Stathopoulos, and Vedolin (2017)), variance risk premia (Della Corte, Sarno, and Tsiakas (2011)) and inflation risk (Jylhä, Suominen, and Lyytinen (2008)).

aversion, belief estimation and probability distortions. In this vein, Dobrynskaya (2014) finds that her estimated downside risk premia for currency returns is in line with the downside risk premia implied by prospect theory.[9] Concerning belief distortions, Barberis and Huang (2008) and Brunnermeier, Gollier, and Parker (2007) show that belief distortions create a preference for positive skewness, which implies higher expected returns for assets with negatively skewed payoffs. Furthermore, Chabi-Yo and Song (2012) find that probability weighting of rare events can explain the time-series and cross-sectional variation of currency returns. However, they use a rank-dependent expected utility (RDEU) model and non-parametric methods to recover the probability weighting implied by currency options. Similarly, Polkovnichenko and Zhao (2013) also use a RDEU model to estimate non-parametric probability weighting functions implied by S&P 500 index options. While the results of Chabi-Yo and Song (2012) are in line with ours, i.e. probability weighting matters for currency carry trade returns, their methodology differs substantially. First, we use a crash-o-phobia asset pricing model instead of a RDEU model and instead of constructing a risk factor, we evaluate the monthly fit of our crash-o-phobia Euler equation. Second, we estimate a parametric probability weighting function proposed by Prelec (1998) and third, we apply the parametric Vanna-Volga method (Castagna and Mercurio (2007)) to recover risk-neutral probabilities from currency options. All in all, we believe that the non-normal characteristics of the return distribution of the carry trade, in particular negative skewness and tail risk, might well be captured by loss aversion and overweighting of rare events with small probabilities.

In terms of methodology, our approach is related to Hens and Reichlin (2013) and Kliger and Levy (2009). Hens and Reichlin (2013) estimate a similar form of the Euler equation with belief distortion and belief estimation but without loss aversion to explain equity data. We extend their model in several dimensions and price currency returns instead of equity returns. While Kliger and Levy (2009) also price equity returns, their focus is on evaluating the performance of different models, such as expected utility framework (EUT), RDEU and cumulative prospect theory (CPT), using information from option markets. They constrain their parameter estimates to be constant over the whole sample period, whereas we reestimate the Euler equation every month to analyse time-series variation. Hence, this paper is the first study to explain currency carry trade returns with a crash-a-phobia asset pricing model, including belief distortion, belief

[9] Dobrynskaya (2014, p.22-23) provides a very nice numerical example to show how her estimated downside risk premia matches the risk premia implied by Kahneman and Tversky's (1979) prospect theory.

estimation and loss aversion. All parameter estimates are implied by financial market data, which allows for a unique angle on time-series and cross-sectional variation of investors' loss aversion and probability weighting with respect to different currencies. Overall, we find that crash-o-phobia matters for the pricing of currency carry trade returns, both in terms of statistical significance as well as economic relevance.

The paper is structured as follows. Section II describes the standard asset pricing model and the different behavioral aspects we use to derive the crash-o-phobia Euler equation. The data, derivation of risk-neutral probabilities and our estimation method is outlined in Section III. In Section IV we describe our main empirical results including robustness tests and model extensions. Section V concludes.

II. Asset Pricing Model

In this section, we describe the asset pricing model with which we test whether crash-o-phobia is a valid explanation for currency carry trade returns. By making certain assumptions on the investor's utility and belief formation process, we can use Euler equations to calculate model-implied state prices. We then compare these implied state prices with state prices derived from option data representing risk-neutral probabilities. If the model-implied and the option-implied state prices are the same or very similar, then, the model is potentially a good explanation for the empirical data. Using this approach, we compare the performance of the standard Euler equation, assuming CRRA utility and rational beliefs, with our proposed crash-o-phobia Euler equation which includes elements of CPT: estimation of probabilities, distortion of probabilities and loss aversion. In the following, we first describe the standard expected utility framework, which we use as benchmark model. Then, we explain the elements necessary to derive our crash-o-phobia model. Finally, we outline the concept behind our two pricing perspectives, i.e. the currency investor and the US investor.

A. Standard approach

The benchmark model of choice is the standard expected utility model with CRRA preferences. We closely follow the two-period model with a representative investor outlined in Hens and Reichlin (2013). We assume that markets are complete and that there is a finite number of possible states, $s = 1, \ldots, S$, in the second period. Further, we assume CRRA utility and rational beliefs for our benchmark expected utility framework. Hence, the first-order condition or Euler equation is

$$\frac{p_s u'(x)}{\sum_s p_s u'(x)} = \pi_s^* \tag{1}$$

$$\text{where} \quad u(x) = \frac{x^{1-\eta}}{1-\eta} \tag{2}$$

and x represent gross returns of the asset which we want to price, p_s are the beliefs on physical probabilities and π_s^* are risk-neutral probabilities, which are equivalent to normalized state prices. Further details on the setup of the standard asset pricing model and the derivation of the first-order condition are given in Appendix A.

B. Crash-o-phobia approach

In many standard asset pricing models it is assumed that agents are risk-averse and hold correct beliefs about future states. These assumptions are reflected in the benchmark model, which we outlined above. We introduce three ways to relax these assumptions in order to capture the non-normal properties of currency carry trade returns: first, loss aversion, second, belief estimation of probabilities, and, third, probability distortion.

B.1. Loss aversion

Loss aversion implies that investors are more averse to losses than they are enticed by gains. It is one of the key elements of Tversky and Kahneman's (1992) cumulative prospect theory. In terms of utility, loss aversion means that marginal utility is higher in the domain of losses than in the domain of gains. Moreover, according to prospect theory investors value gains and losses and not the overall wealth level. Hence, the utility function is applied to asset returns instead of wealth levels. The original loss averse utility function proposed by Kahneman and Tversky (1979) is convex over losses and concave over gains. Additionally, it has a kink at the reference point.

To ensure a global maximum and differentiability at the reference point, we use the loss averse utility function proposed by Rosenblatt-Wisch (2008)

$$u(x) = (x - 1)\left(1 + \frac{\delta}{1 + e^{\kappa(x-1)}}\right) \tag{3}$$

where κ is the speed of the switching and δ the degree of loss aversion. Note that we shifted the fixed reference point from 0 to 1, since we work with gross returns. Figure 1 plots the loss averse utility function with a κ of 20 and a δ of 0.5. (The size of κ was chosen due to the scaling of the data and the size of δ because 1.5 is a typical value for the loss aversion found in experiments.) One can clearly see the increase in marginal utility left of the reference point.

[Figure 1 about here.]

B.2. Belief estimation

Besides introducing loss aversion, we relax a standard assumption on belief formation: It is often assumed that agents base their beliefs on historical data (Ziegler (2006)). To capture belief formation processes other than the forward projection of past realizations, we follow Ziegler (2006) and Hens and Reichlin (2013) and assume that investors have lognormal beliefs about future returns

$$p_s = \frac{1}{x\sigma\sqrt{2\pi_s}} \exp\left(-\frac{(\ln(x) - \mu)^2}{2\sigma^2}\right) \tag{4}$$

where x represents past gross returns. Thus, the beliefs are specified by μ and σ, i.e. $p_s \sim \mathcal{LN}(\mu, \sigma)$. We refer to this phenomenon as belief estimation.

B.3. Probability distortion

The third extension which we introduce, is probability distortion: According to cumulative prospect theory (Tversky and Kahneman (1992)) agents overweight extreme events that occur with small probability. In the context of our model, this means introducing probability distortion relative to the lognormal beliefs. Thus, we allow for beliefs that put more weight on tail events compared to a lognormal distribution.

To model these probability distortions we use the the two parameter probability weighting function proposed by Prelec (1998) applied separately to gains and losses.[10]

$$T(p_s) = \begin{cases} \exp(-\beta^{+}(-\ln(p_s))^{\gamma}) & \text{if } x \geq 0 \\ \exp(-\beta^{-}(-\ln(p_s))^{\gamma}) & \text{if } x < 0 \end{cases} \tag{5}$$

with $0 < \gamma < 1$ and $\beta^{+}, \beta^{-} > 0$. The parameter γ captures convexity, and β^{+} and β^{-} control the inflection point. The probability weighting function is typically applied to cumulative probabilities. Figure 2 plots this probability weighting function with a γ of 0.5 and a β of 0.8, which are values typically found in experiments. These distortions imply that small probabilities are substantially overweighted while large probabilities are underweighted.

[Figure 2 about here.]

B.4. Crash-o-phobia asset pricing model

Including all three crash-o-phobia aspects—loss aversion, belief estimation and probability distortion—in the standard expected utility first-order condition given in equation (1), results in the following crash-o-phobia Euler equation

$$\frac{u'(x) p_s T'\left(\sum_{i=1}^{s} p_i\right)}{\sum_{s=1}^{S} u'(x) p_s T'\left(\sum_{i=1}^{s} p_i\right)} = \pi_s^{*} \tag{6}$$

$$\begin{aligned} \text{where} \quad u(x) &= (x-1)\left(1 + \frac{\delta}{1+e^{\kappa(x-1)}}\right) \\ T(p_s) &= \begin{cases} \exp(-\beta^{+}(-\ln(p_s))^{\gamma}) & \text{if } x \geq 0 \\ \exp(-\beta^{-}(-\ln(p_s))^{\gamma}) & \text{if } x < 0 \end{cases} \\ p_s &\sim \mathcal{LN}(\mu, \sigma) \end{aligned}$$

and p_s are the beliefs on historical probabilities and π_s^{*} represent risk-neutral probabilities. Note that the probability weighting function is applied to the cumulative sum of individual probabil-

[10] See Fehr-Duda and Epper (2012) for an overview and evaluation of different probability weighting functions. According to their study, the two parameter probability weighting function of Prelec (1998) has the most realistic as well as best numerical properties.

ities, i.e. $T(\sum_{i=1}^{s} p_i)$.[11] In line with our definition of crash-o-phobia, as the combination of loss aversion and probability weighting, we claim that we find evidence in favor of crash-o-phobia if γ is significantly smaller than 1 and δ greater than 0.

C. Investor perspective

To estimate the crash-o-phobia asset pricing model, it is important to determine the state prices that the agent uses to price the assets. As we focus on currency markets, we take the perspective of a currency investor. We assume that the currency investor predominantly consumes currency returns and that thus his state prices are determined by these returns. In this case, the state space is defined by foreign exchange options on the same currency the investor prices. Thus, the risk-neutral probabilities are currency specific and derived from foreign exchange options, denoted by $\pi_s^{*,FX}$. We assume that the state space is fully spanned by the currency options. We take the view of a currency investor because we are interested in currency specific behavioral phenomena rather than an investor's consumption portfolio. In particular, is a hedging currency priced differently compared to a risky high interest currency? This approach allows as well for substantial cross-sectional variation since the state space and risk-neutral probabilities are different for each currency. Hence, we can investigate time-series and cross-sectional variation in parameter estimates.

The currency markets are generally believed to be driven by large and professional investors (Cheung and Chinn (2001)) sometimes termed intermediaries (Gabaix and Maggiori (2015)). When taking the view of the currency investor, we thus have to think about whether, first, loss aversion and, second, probability weighting are sensible assumptions for these kind of investors. Regarding loss aversion, experiments (Haigh and List (2005)) have shown that professional investors depict an even higher loss aversion than students in experiments. One potential reason for this are value-at-risk constraints that investors have (Campbell, Huisman, and Koedijk (2001)). Thus, it seems very realistic that currency investors are loss averse.

[11]The decision weights in the original version of Tversky and Kahneman's (1992) cumulative prospect theory are defined as the difference between two probability weighted cumulative probabilities. The decision weight applied to the outcome in state s is $T\left(\sum_{i=1}^{s} p_i\right) - T\left(\sum_{i=1}^{s-1} p_i\right)$. Due to numerical instabilities we approximate this first difference by a first order Taylor approximation, similar to Hens and Reichlin (2013). Hence, our decision weight applied to the outcome in state s is $p_s T'\left(\sum_{i=1}^{s} p_i\right)$.

Regarding the probability distortions, it is important to keep in mind that we introduce this probability weighting relative to a lognormal distribution. For currency returns, it is very likely that investors have beliefs deviating from the lognormal distribution as the currency carry trade returns have highly non-normal characteristics. We model these beliefs using probability weights on the lognormal distribution instead of using a different class of distributions. This allows us to model the weights on gains and losses separately and to compare our results with other studies related to prospect theory. Overall, loss aversion and probability weighting relative to the lognormal distribution seem to be realistic assumptions for professional currency investors.

As an extension, we show that the results are very similar when taking the perspective of a US investor, similar to the approach of Hens and Reichlin (2013) or Kliger and Levy (2009). We assume that the there is just one representative investor with certain preferences and beliefs who prices several other assets (i.e. currencies). The US investor consumes predominantly US equity returns which we proxy by the S&P 500 returns. The state prices are therefore defined by the returns of the SP500 index. In this case, the state space is defined by one asset (the S&P 500) and used to price another asset (a currency). The US investor perspective allows us to investigate whether the state prices implied by the S&P 500 can explain currency carry trade returns of various currencies. The details of this approach are given in Section IV.C.

III. Data and Estimation Method

Our data set consists of 10 different currencies which are CHF, EUR, GBP, YEN, NOK, BRL, ZAR, RUB, INR and MXN. All currencies are denoted vis-à-vis the USD. We choose 5 developed and 5 emerging market currencies to cover a broad spectrum of high- and low-interest rate currencies.[12] The focus of this paper is on pricing currency returns to identify different behavioral characteristics and not on developing currency trading strategies or analysing diversification potentials. Hence, the choice of currencies as well as the sample size should be representative and not exhaustive. Furthermore, the sample period is restricted by the availability of currency options data, in particular across different strike prices. To estimate the crash-o-phobia Euler equation, we fit option-implied risk-neutral probabilities observed at the end of month t to past currency returns over a lookback period of 5 years. Therefore, the sample period for spot and

[12]The classification between developed and emerging market countries closely follows the Morgan Stanley market classification which can be found at `https://www.msci.com/market-classification`.

forward rates to calculate returns for each currency starts 5 years before the first currency option data is available. The exact starting dates are summarized in the last two columns of Table I. All data end in June 2016.

A. Currency carry trade returns

We collect monthly data on spot and one-month forward exchange rates from Datastream over the currency specific time periods given in Table I. Let s_t be the log spot rate and f_t the log one-month forward exchange rate. Both rates are denoted as units of US dollars per foreign currency, i.e. an increase in the spot rate means an appreciation of the foreign currency. The currency return is what an investor earns from buying the foreign currency in the forward market and selling it in the spot market after one month or equivalently, you can borrow in the domestic currency and invest in the foreign currency. Hence, the log excess return on a currency is defined as

$$rx_{t+1} = s_{t+1} - f_t \tag{7}$$

This expression can be extended by adding and subtracting the current spot rate, $rx_{t+1} = \Delta s_{t+1} + s_t - f_t$, where $\Delta s_{t+1} = s_{t+1} - s_t$ and $s_t - f_t$ is called the forward discount or premium, respectively. Assuming that the covered interest parity (CIP) holds,[13] i.e. $s_t - f_t = i_t^* - i_t$ where i_t^* and i_t are the foreign and domestic one-month interest rates, results in

$$rx_{t+1} = \Delta s_{t+1} + (i_t^* - i_t) \tag{8}$$

The first part, Δs_{t+1}, represents the realized currency return which comprises the uncertainty about future appreciation or depreciation of the foreign currency vis-à-vis the US dollar. The second part, $i_t^* - i_t$, refers to the interest rate differential between the two currencies and it is also called the carry. Since the carry is known ex-ante, the uncertainty about the future exchange rate is the only source of risk driving currency returns.

[13] Akram, Rime, and Sarno (2008) show that the CIP is violated only at very high frequencies, but it holds at daily or lower horizons. Du, Tepper, and Verdelhan (2018) further show that CIP deviations persist in the post crisis period. Nevertheless, we choose to calculate the carry trade returns using the interest rates instead of the forward rate.

This decomposition shows that the carry (representing the interest rate differential) is already included in currency excess returns. Thus, we refer to the currency returns defined in equation (7) as *currency carry trade returns*.[14] Note however that we always take a long position in the foreign currency and short the US dollar which implies that there is no sorting based on the forward discount or premium. Moreover, we investigate the carry trade returns of each currency separately and do not sort them cross-sectionally or aggregate individual currencies to a carry trade portfolio. All currency carry trade returns are denominated in US dollars.

Table I reports summary statistics for all 10 monthly currency return time-series. While the annualized mean return of most developed market currencies is on average negative, it is substantially higher and positive for all emerging market currencies, except the Russian ruble. During our sample period, the best risk-adjusted performance—measured by the highest Sharpe ratio—was achieved by an investment in the Brazilian real. Currency carry trade returns are clearly negatively skewed, except the Swiss franc, which is known as a safe haven currency, as well as the South African Rand, which appears to have positively skewed excess returns during our sample period. Moreover, the excess kurtosis is positive for all 10 currency returns indicating the presence of fat tails. Overall, these currency carry trade returns are obviously not normally distributed and there is substantial cross-sectional variation.

B. Risk-neutral probabilities

To estimate the Euler equation we further need risk-neutral probabilities. These probabilities can be calculated from option prices.

We derive risk-neutral probabilities from foreign exchange options for each currency. According to FX market conventions, we download for each currency the following end-of-month volatility quotes from Bloomberg (European style, one month to maturity): at-the-money volatility, 25-delta-call strangle and 25-delta-call risk reversal.[15] A long strangle consists of a long out-of-the money call and a long out-of-the money put option. A long risk reversal buys an out-of-the money call and shorts an out-of-the money put option. Again, all foreign exchange options are

[14] We use the two terms currency returns and currency carry trade returns interchangeably and always refer to the log excess returns defined in equation (7).

[15] Currency options are quoted for different deltas instead of strike prices and the current prices are given in terms of implied volatilities. The delta of a call option is the first derivative of the Black-Scholes price with respect to the spot price. Moreover, traded FX options are usually quoted as a combination of individual call and put options.

quoted vis-à-vis the US dollar and we use the same denomination as USD per one foreign currency unit. Furthermore, we assume that the CIP holds and hence, we only need the one month US interbank rate from Bloomberg since we can back out the foreign interest rate using forward and spot exchange rates. Depending on the currency, the sample period starts between 2003 and 2009 and ends in June 2016, where exact dates are specified in the last column of Table I.

To calculate risk-neutral probabilities we use the Vanna-Volga method (Castagna and Mercurio (2007)) which allows to infer an implied volatility smile from these three commonly traded quotes in foreign exchange option markets. The idea is to construct a locally replicating portfolio whose associate hedging costs are added to the corresponding Black-Scholes prices in order to produce smile-consistent values. Since these market quotes are a combination of different call and put options, the first step is to solve for the implied volatilities of a 25-delta-put options and a 25-delta-call option. Note that the at-the-money volatility is already given, which in total results in three volatility data points. Next, these implied volatilities are used to calculate strike prices corresponding to the deltas which is done via the Garman and Kohlhagen (1983) version of the Black-Scholes option pricing formula. We use the exact version of the Vanna-Volga scheme to inter- and extrapolate the implied volatility curve across a fine grid of strike prices and to infer the corresponding call option prices.[16] Last, we calculate normalized risk-neutral probabilities using the results of Breeden and Litzenberger (1978) via the second derivative of call option prices. Overall, we estimate a separate risk-neutral distribution for each currency and every month.

C. First-order condition estimation

The general form of the crash-o-phobia Euler condition is given in equation (6), which we estimate every month and for every currency using non-linear least squares. That is, we minimize the squared distance between the actual risk-neutral probabilities observed in the market and the model-implied normalized state prices. Let $\Theta_1 = \delta, \kappa$, be the parameters of the utility function, $\Theta_2 = \mu, \sigma$, the parameters of the lognormal distribution modelling the estimated beliefs and $\Theta_3 = \gamma, \beta^+, \beta^-$, the parameters of the probability weighting function. We allow for cross-sectional variation, i.e. the parameter estimates can vary across currencies. Moreover, every month

[16] Castagna and Mercurio (2007) also provide a first- and second-order approximation of there implied volatility surface which is computationally easier and faster. However, we find that it puts too much weight on the tails of the distribution and the fit is not very good.

we take gross currency returns over a lookback period of 5 years, sort them in ascending order, $x_1^{FX}, \ldots, x_s^{FX}, \ldots, x_S^{FX}$, and fit them to the end-of-month normalized state prices. The actual risk-neutral probabilities are derived from 1-month option prices observed at the end of month t from where we start the lookback period of currency returns. Hence, we use past return data and forward looking option data to estimate the investor's preferences and beliefs. Further note that there is no look ahead bias, since all data is available at the end of month t. Formally, we can write the crash-o-phobia Euler equation as a non-linear regression model as follows

$$\pi_{s,j}^{*,FX} = \frac{u'(x_{s,j}^{FX};\Theta_{1,j})\, p(x_{s,j}^{FX};\Theta_{2,j})\, T'\left(\sum_{i=1}^{s} p(x_{i,j}^{FX};\Theta_{2,j});\Theta_{3,j}\right)}{\sum_{s=1}^{S} u'(x_{s,j}^{FX};\Theta_{1,j})\, p(x_{s,j}^{FX};\Theta_{2,j})\, T'\left(\sum_{i=1}^{s} p(x_{i,j}^{FX};\Theta_{2,j});\Theta_{3,j}\right)} + \varepsilon_{s,j} \tag{9}$$

$$\min_{\Theta_{1,j},\Theta_{2,j},\Theta_{3,j}} \quad \sum_{s=1}^{S} \varepsilon_{s,j}^2 \qquad \text{for } j = 1, \ldots, 10 \tag{10}$$

Note that we left out the subscript t, but of course we estimate the non-linear regression model (9) every month.

IV. Empirical Results

In the following, we present the empirical results from estimating the parameters of the Euler equation by non-linear least squares as outlined in Section III. First, we describe the results of the standard model and, second, the results of the crash-o-phobia model. Third, we show that the crash-o-phobia results hold even when we assume the perspective of a US investor instead of a currency investor. The benchmark model refers to equation (1), i.e. CRRA utility, rational beliefs and no probability distortions, while the crash-o-phobia model given by equation (6) always includes loss aversion, belief estimation and probability weighting. The analysis shows that the crash-o-phobia model explains currency carry trade returns well and offers a statistically significant improvement compared to the standard model.

A. Standard model as a benchmark

First, we estimate the standard model given in equation (1), which later serves as a benchmark to assess the performance of the crash-o-phobia model. We graphically evaluate the fit by comparing the option-implied risk-neutral density with the model-implied risk-neutral density. The model performs well, if these two densities are very similar. Figure 3 shows the option-implied density (black dashed line) and normalized state prices implied by the model with CRRA utility and rational beliefs (red line) for October 2008 and October 2012 for all ten currencies. The option-implied risk-neutral densities are estimated from currency options and the model-implied densities are calculated according to the left-hand side of equation (1). For both dates, October 2008 and October 2012, it is evident that the empirical model fit is not good. Comparing the plots for 2008 with the plots for 2012 reveals that the performance of the standard model is worse in times of crises (2008) than in relatively calm times (2012). In brief, the standard model is not able to explain currency carry trade returns. The difficulties of the model to explain the data are more accentuated in times of crises.

[Figure 3 about here.]

B. Crash-o-phobia model

This section presents the results from estimating the crash-o-phobia model according to equations (9) and (10). We first describe the average parameter estimates over time, then the time-series variation of the estimated parameters and finally we compare the performance of the crash-o-phobia model with the benchmark model. Furthermore, we test whether the crash-o-phobia parameter estimates can explain higher moments of currency carry trade returns, in particular skewness and kurtosis, both in the cross-section as well as time-series. Last, we construct currency investment strategies using our parameter estimates as cross-sectional sorting characteristics.

B.1. Average parameter estimates

Every month we estimate equation (9) to price past currency carry trade returns over a lookback period of 5 years. As a result, we obtain monthly parameter estimates of $\Theta_{1,j}, \Theta_{2,j}, \Theta_{3,j}$ for each currency which allows us to analyze currency specific behavioral phenomena. Overall, our parameter estimates reveal significant evidence in favor of crash-o-phobia: currency investors exhibit substantial loss aversion ($\delta > 0$) and significantly overweight extreme events ($\gamma < 1$).

First, we focus on cross-sectional differences across our sample of developed and emerging market currencies. Table II summarizes the time-series average of each parameter estimate together with the corresponding standard errors denoted in brackets.[17] Results for developed market currencies are given in Panel A and the estimates for emerging market currencies in Panel B. We find that all parameter estimates are highly significant at the 1 % confidence level, where we test the parameters of the utility function, $\Theta_{1,j}$, and lognormal distribution, $\Theta_{2,j}$ against the null hypothesis of 0 while the parameters of the probability weighting function, $\Theta_{3,j}$, are tested against 1. The currency specific means of the lognormal distribution characterizing the agent's beliefs, μ, are slightly negative and on average they are lower for emerging market currencies than for developed markets. On the contrary, the agent's estimates of the volatility parameter, σ, are fairly similar across the two subsamples of currencies.[18]

Regarding the probability distortions implied by the different currency carry trade returns, we obtain substantial cross-sectional variation in parameter estimates. For example, the parameter γ which captures convexity varies between 0.4469 (NOK) and 0.7124 (YEN) for the developed market currencies while it ranges from 0.2518 (ZAR) to 0.4591 (INR) for the emerging market currencies. Hence, the average γ of developed market currencies is higher than those of emerging market currencies implying a much stronger overweighting of small probabilities for the latter. A γ smaller than 1 implies that currency investors put more weight on the tail probabilities relative to the lognormal distribution. According to the estimated values, this effect is more accentuated for emerging market currencies. These findings are in line with the survey results on international risk sharing conducted by Rieger, Wang, and Hens (2017), who find that wealthier countries exhibit less probability weighting. Very similar numbers for γ have been found in experiments, where the estimated values range from 0.44 to 0.74 (Gonzalez and Wu (1999), Fehr-Duda and Epper (2012), Wu and Gonzalez (1996)). Polkovnichenko and Zhao (2013), who use stock market data, find values between 0.563 and 1.64,[19] which is as well consistent with our findings. The estimates for β^- and β^+ are range between 1.76 and 2.44. In experiments, these values were between 0.7 and 1.2. Given the highly non-normal return characteristics of the carry trade returns, it makes

[17]We calculate standard errors according to the Fama and MacBeth (1973) method. Since we estimate the Euler equation every month, we get a time-series of parameter estimates of which we can calculate sample averages and standard deviations. Let $\hat{\mu}_t$ be a time-series of estimated parameters. Then, our time-series average is given by $\hat{\mu} = \mathbb{E}[\hat{\mu}_t]$ and the standard error is $\sigma(\hat{\mu}) = \sqrt{\frac{Var(\hat{\mu}_t)}{T}}$.

[18]Note that μ and σ are parameters of the lognormal distribution and not equal to the (average) monthly mean and standard deviation of past currency returns. These are given by $\mathbb{E}[x] = \exp\left(\mu + \frac{\sigma^2}{2}\right)$ and $Std(x) = \sqrt{\exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)}$. Hence, a negative value for μ, does not imply that currency returns are on average negative.

[19]In contrast to many other approaches they allow for $\gamma > 1$.

however sense that our β estimate is higher, which means relatively more weight is placed upon very extreme outcomes. Overall, the β^- and β^+ are very similar and thus the model nearly collapses to a one parameter specification of the probability weighting function.

To quantify the implied loss aversion, we evaluate the utility function at a loss of 30 % using the estimated parameter values of δ and κ and the results are reported in the last column of Table II. Again, we obtain substantial cross-sectional variation where the average loss aversion of developed market currencies is higher than the loss aversion implied by emerging market currency returns. In line with expectations, the highest values are found for the CHF (2.8301) and the YEN (3.5897)—two currencies which are commonly referred to as safe haven currencies. Regarding our crash-o-phobia explanation of currency returns, these high values of implied loss aversion indicate that investors holding the CHF or the YEN are really afraid of severe currency crashes, i.e. they fear losses, hence they invest in safe haven currencies. One apparent outlier to these results is the Indian Rupee, where investor have a loss aversion of 2.69. This can be explained by the fact that the Indian Rupee is a managed float and thus the risk of a large crash is very limited in this currency. The values for loss aversion are as well in line with findings from experiments. For example, the loss aversion estimated by Kahneman and Tversky (1979) using a similar utility function was 2.25. In further experiments Abdellaoui, Bleichrodt, and Paraschiv (2007) find values ranging between 1.19 and 2.34, which is as well very close to our results. Using empirical data Kliger and Levy (2009) get parameters ranging between 1.163 and 1.406. Our estimated parameters for loss aversion are thus in line with experimental data and moreover, they accurately identify safe haven currencies.

To sum up, we document significant evidence in favor of crash-o-phobia across all currencies, i.e. $\gamma < 1$ and $\delta > 0$. In particular, developed market currencies exhibit less probability over-weighting but higher loss aversion, while the reverse is true for emerging market currency returns. Moreover, we conclude that the crash-o-phobia component of carry trade returns is currency specific, at least from the viewpoint of a currency investor, and it varies across currencies.

B.2. Time-series variation in parameter estimates

The use of financial market data as opposed to experiments, allows us to we investigate the time-series variation of these currency specific parameter estimates. In particular, we can analyze in which states of the world crash-o-phobia strongly influences market perception or not.

However, given that our expectation horizon is one month—determined by the option maturity—we expect to see quite some time-series variation in parameter estimates. Furthermore, we want to avoid strong parameter restrictions, but instead allow the model to capture the most possible information from market data. Therefore, we use a one month horizon and reestimate the Euler equation every month. Given the market implied belief and preference parameters, we can then verify whether these estimates over time are reasonable. In the previous section, we have shown that on average our parameter estimates are realistic and economically relevant. Moreover, the standard errors in Table II, which measure the variation in monthly parameter estimates, are relatively small such that all estimates are statistically significant. Nevertheless, the time-series analysis of parameter estimates reveals some interesting patterns in crash-o-phobic preferences and beliefs, but overall crash-o-phobia is present at all time periods.

In Figure 4 we plot the time-series of monthly parameter estimates for the implied loss aversion at 30 % and the probability weighting parameter γ. The first row in each Panel always refers to the developed market currencies, while the second row includes estimates of emerging market currencies. Regarding the implied loss aversion (top Panel), we can observe that the average level is higher for developed market currencies than emerging market currencies across the whole sample period. Nevertheless, there are some distinct spikes during currency specific or other economic crises. The time-series plots of the probability weighting parameter γ reveal a similar picture (bottom Panel). The average level is lower for emerging market currencies implying stronger overweighting of small probabilities compared to developed market currencies. Moreover, at times of crises or when currency investors fear a severe crash or a strong devaluation of the specific currency against the USD, we can observe a sudden drop in γ.

[Figure 4 about here.]

Figure 5 plots the investor's beliefs over time. The top panel shows the time-series of estimated means of the lognormal distribution, revealing quite some fluctuations and in particular for emerging market currencies it is mostly negative. However, this does not imply that currency returns are negative on average, since the parameter μ is not equal to the expected value of a lognormally distributed variable. Moreover, the estimates for μ are very sensitive to changes in σ as well as β^+ and β^- of the probability weighting function. Hence, the economic interpretation of μ is not as straight forward given that we maximize the overall fit. Besides some currency specific events, we observe a general increase in uncertainty and crash-o-phobic phenomena around the financial crisis of 2008. In particular, the bottom Panel of Figure 4 reveals a substantial spike in the volatility of currency carry trade returns across all currencies. Related to this observation, Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2015) find that the fall of 2008 appears as a turning point in currency option markets. Before the crises, foreign exchange option smiles were fairly symmetric, while after 2008 option smiles became clearly asymmetric. They argue that these asymmetries depend on the interest rate level, where high interest currencies reflect the risk of large depreciation during bad times and hence, the smile is skewed. In a similar vein, Brunnermeier, Nagel, and Pedersen (2008) find that after a currency crash, speculators are willing to pay more for crash insurance which increases its price. This crash risk insurance is reflected by currency risk reversal options. Thus, after a crisis the price of currency risk reversal options increase which translates into an increased negative skewness of the corresponding risk-neutral distribution. Our results are in line with these findings in the literature. In particular, we document that after a crash people become more loss averse and increase the overweighting of small probabilities, which can reconcile the rise in negative skewness and tail risk of currency carry trade returns.

[Figure 5 about here.]

Regarding the fit and ability of the crash-o-phobia model to capture non-normal properties of currency returns, we plot the model-implied and the option-implied risk-neutral probability distribution for each currency at two specific points in time. Figure 6 shows these plots for October 2008 and October 2012. Obviously, the fit of our model at times of crises, i.e. in October 2008, is less good than at normal times, such as in October 2012. The latter fit is very precise for the developed market currencies and fairly good for emerging market currencies.

[Figure 6 about here.]

B.3. Model comparison

In order to better evaluate the performance and fit of our crash-o-phobia model, other than just graphically investigating distributional plots, we do a statistical model comparison between the crash-o-phobia model and different benchmark cases. In addition, we analyze how much each behavioral aspect contributes to the overall explanatory power of the crash-o-phobia model. Our benchmark model assumes CRRA preferences and a belief formation according to historic data, i.e. rational beliefs. We compare it to the following subversions of our crash-o-phobia model: first, the model with CRRA utility and only belief estimation (CRRA.mis), second, the model with CRRA utility, belief estimation and probability weighting (CRRA.dismis). Third, we add loss aversion which results in our crash-o-phobia model. To compare the fit of these models while correcting for the degrees of freedom due to the increased number of free parameters, we calculate the Akaike information criterion (AIC) (Akaike (1998)) for each of them. The AIC measures the error of a model while correcting for the degrees of freedom and it is calculated as follows

$$AIC = n * \log\left(\frac{RSS}{n}\right) + 2k \tag{11}$$

where n is the number of observations, RSS is the sum of squared residuals from the estimation, and k are the degrees of freedom of the model, i.e. the number of parameters estimated. The lower the AIC, the better the fit of the model.

In Table III we first report the average AIC for each currency. For all currencies, the AIC decreases with each element we add to the model. Hence, each crash-o-phobia aspect improves the fit of the overall model, even after correcting for the degrees of freedom. In absolute terms, our proposed crash-o-phobia model with loss aversion, belief estimation and probability weighting delivers the best fit across all currencies, i.e. it has the lowest AIC. We further calculate the number of months (expressed as percentage points) in which the AIC of the crash-o-phobia model is smaller than the AIC of a given benchmark model, measuring the performance in relative terms. The crash-o-phobia model outperforms the CRRA benchmark model every months for all currencies implying a ratio of 100 %. It outperforms the CRRA model with belief estimation in over 90 % of months across currencies and if we further add probability weighting, the crash-o-phobia model is still better in around 80 % of cases. Thus, in relative terms the crash-o-phobia model beats all subversions in 80-90 % of months. Furthermore, to test the statistical significance of these fit improvements, we use the Kolmogorov-Smirnov test. It analyzes whether the model-implied risk-neutral density is sufficiently similar to the actual option-implied risk-neutral density. Again, we report the number of months (given in percentage points) for which the null hypothesis—that the two distributions are equal—is rejected at a 5 % confidence level. Hence, a high number means that the distribution implied by a given model is statistically different from the observed true risk-neutral density. For the CRRA benchmark model, this hypothesis on the equality of distributions is rejected in 100% of cases for all currencies. In contrast, for the crash-o-phobia model the equality of distributions cannot be rejected in 100% to 60% of cases. This means that most of the time, the distribution implied by the crash-o-phobia model is statistically not different from the option-implied distribution. In the cross-section, the fit of the crash-o-phobia model is slightly better for developed market currencies than for emerging market currencies. Overall, the crash-o-phobia model has the best explanatory power even when controlling for the increased number of free parameters.

B.4. Explaining higher moments of currency returns

We have motivated our crash-o-phobia model as a possible explanation for the non-normal characteristics of currency returns. The time-varying currency risk premia allowed us to characterize the beliefs and preferences of the agents holding them. Now, we verify whether the estimated crash-o-phobia parameters actually explain these non-normal currency return properties. Using a standard time-series and cross-sectional asset pricing approach, we test whether our estimated parameters explain the skewness and kurtosis of currency carry trade returns.

First, we calculate for each currency the skewness and excess kurtosis of monthly returns over a rolling lookback window of 5 years. These are denoted as $skew_{t,i}$ and $kurtosis_{t,i}$ for currency i at month t. For the time-series test, we run the following time-series regressions for each currency i

$$skew_{t,i} = \alpha_{0,i} + \alpha_{1,i}\gamma_{t,i} + \alpha_{2,i}\beta^{-}_{t,i} + \alpha_{3,i}LA_{t,i} + \varepsilon_{t,i} \tag{12}$$

$$kurtosis_{t,i} = \alpha_{0,i} + \alpha_{1,i}\gamma_{t,i} + \alpha_{2,i}\beta^{-}_{t,i} + \alpha_{3,i}LA_{t,i} + \varepsilon_{t,i} \tag{13}$$

where $t = 1, \ldots, T$. The regressors $\gamma_{t,i}, \beta^{-}_{t,i}$ and $LA_{t,i}$ are the parameter estimates of the crash-o-phobia model. We want to focus on the explanatory power of loss aversion and probability weighting and therefore, we do not include the parameters μ and σ of the belief estimation in these time-series regressions. Moreover, to avoid problems of multicollinearity, we only include

β^- in the regression model.[20] For the cross-sectional asset pricing test, we follow the Fama and MacBeth (1973) approach and estimate the following regressions for every month t

$$skew_{t,i} = \alpha_{0,t} + \alpha_{1,t}\gamma_{t,i} + \alpha_{2,t}\beta^-_{t,i} + \alpha_{3,t}LA_{t,i} + \varepsilon_{t,i} \tag{14}$$

$$kurtosis_{t,i} = \alpha_{0,t} + \alpha_{1,t}\gamma_{t,i} + \alpha_{2,t}\beta^-_{t,i} + \alpha_{3,t}LA_{t,i} + \varepsilon_{t,i} \tag{15}$$

where $i = 1, \ldots, 10$. In contrast to the time-series approach, we now get coefficient estimates every month. The average coefficient as well as there standard error are then calculated as the sample average

$$\hat{\alpha}_0 = \mathbb{E}[\hat{\alpha}_{0,t}] = \frac{1}{T}\sum_{t=1}^{T}\hat{\alpha}_{0,t} \tag{16}$$

$$\sigma(\hat{\alpha}_0) = \frac{\sigma(\hat{\alpha}_{0,t})}{\sqrt{T}} \tag{17}$$

which also holds for all other regression coefficients $\alpha_{1,t}, \alpha_{2,t}$ and $\alpha_{3,t}$. The results are summarized in Table IV.

First, in the time-series dimension we observe that all crash-o-phobia parameters have a positive effect on the skewness of currency returns, while they have a significantly negative effect on excess kurtosis. Hence, a higher γ estimate—implying less probability weighting of extreme events—and a higher loss aversion, are related to positive skewness and negative excess kurtosis of currency carry trade returns. This relation holds across most currencies. Regarding the non-normal properties of currency returns, we can conclude that in the time-series, positive skewness is explained by high loss aversion and weak probability weighting, while high excess kurtosis is explained by low levels of loss aversion but strong probability weighting. The explanatory power of our crash-o-phobia parameters for these non-normal properties—measured by the adjusted R^2—varies between 0 up to 40 % depending on the currency

Second, the cross-sectional analysis shows that loss aversion and probability weighting is also priced in the cross-section of higher currency moments. As expected, currencies for which we estimated a higher γ and β^-—implying a lower degree of probability distortion—have a more positive skewness. Similarly, positive skewness is also related to higher estimates of loss aversion. Correspondingly, higher estimates for γ and β^-, i.e. less probability distortion, and a higher loss

[20]The results are robust to using β^+ or β^-, since they are highly correlated.

aversion are associated with lower excess kurtosis. Overall, agents with high loss aversion and low overweighting of extreme events seem to invest in currencies with a more positive skewness and a lower excess kurtosis—two properties of safe haven currencies.

B.5. Investment strategies

After having documented that the estimated parameters are closely related to the higher moments of currency returns, we now show that crash-o-phobic beliefs and preferences can also help to understand traditional carry trade strategies. Using the ten currencies in our data set, we calculate the returns from a traditional carry trade strategy, a momentum strategy, a strategy based on loss aversion and a strategy based on probability weighting. Every month we sort all currencies into two portfolios according to the selected characteristic at time t (forward discount, past return, probability weighting, loss aversion). Then, we go long in one portfolio and short the other one. We hold this long-short portfolio for one month until $t+1$, and rebalance the portfolio next month according to the characteristic in $t+1$. We neglect transaction costs for all strategies. For the carry trade strategy, we sort the currencies on their forward-spot spread $(s_t - f_t \approx i_t^* - i_t)$ and we go long currencies with the highest interest rate differentials and short the ones with the lowest interest rate differentials. For the momentum portfolio, we buy the currencies that performed best in the last month and sell the past month's losers. For the probability weighing portfolio, we buy currencies for which we estimated a low value of γ (strong probability weighting) and short the currencies with a high value of γ (weak probability weighting). Finally, for the loss aversion portfolio, we take a long position in the currencies for which we estimated the lowest values of loss aversion and go short in the currencies with the highest values of loss aversion. The returns of these long-short portfolios are plotted in Figure 7 and Table V summarizes their performance giving the relevant summary statistics.

[Figure 7 about here.]

First, the performance of the probability weighting strategy is not very attractive. Except the two peaks in 2008 and 2015, its cumulative returns are on a steady decline. In contrast, the carry trade strategy, the momentum strategy and the loss aversion strategy deliver positive returns. The loss aversion strategy outperforms the carry trade strategy and the momentum portfolio in terms of mean return and Sharpe ratio (see Table V). Interestingly, the return correlation between the traditional carry trade strategy and our loss aversion strategy is quite high with 61 % , whereas the correlation between the loss aversion strategy and the momentum portfolio is very low and even negative with -8 %. Sorting on the interest rate differential apparently delivers very similar returns as when we sort on loss aversion. Thus, the loss aversion parameter might offer a possible interpretation of the otherwise rather technical HML factor proposed by Lustig, Roussanov, and Verdelhan (2011).

C. US Investor perspective

So far, we have analyzed crash-o-phobia from the perspective of a currency investor. In this section, we change the perspective and think of the representative US investor whose state prices price all assets. We want to show that evidence of crash-o-phobia is robust to changes in the assumptions on the investor perspective. Furthermore, this assumption of one representative US investor is also more common in the standard asset pricing literature (see for example Lustig and Verdelhan (2007) or Hens and Reichlin (2013)).

Specifically, we assume that this US investor consumes predominantly US equity returns and we proxy his portfolio by the S&P 500. The returns on the S&P 500 determine the state prices and we assume that the state space is fully spanned by S&P 500 options. There is thus just one investor with certain preferences and beliefs who prices several other assets. In our model, this US investor now wants to price different currencies. The state space is therefore defined by one asset (the S&P 500) and used to price other assets (i.e. currencies). The question we investigate is whether the state prices implied by the S&P 500 can explain currency carry trade returns of various currencies.

The difference between the perspective of a currency and a US investor with respect to the crash-o-phobia Euler equation given in equation (6) is the following. In the first case—the currency investor perspective—the risk-neutral probabilities are currency specific and derived from foreign exchange options, denoted by $\pi_s^{*,FX}$. In the second case—the US investor perspective—we use risk-neutral probabilities derived from S&P 500 options. Hence, they are denoted as $\pi_s^{*,SP}$ and they are the same for every currency being priced.

Moreover, the US investor approach allows us to find a unified set of crash-o-phobia characteristics pricing all currencies at once. Therefore, we restrict the estimated parameters to be the same across all currencies while we allowed for cross-sectional variation in the currency investor setting. This results in only one set of parameters pricing all currency returns and there is no cross-sectional variation.

C.1. State space matching

As mentioned above, for the US investor perspective the state space is defined by the S&P 500. Hence, the risk-neutral probabilities and physical probabilities are calculated from data on the S&P 500. However, the agent prices currency carry trade returns, x_{FX}. To estimate the Euler equation, we need to know what currency return an agent expects in a state defined with respect to the S&P 500. For example, what currency return is expected when the S&P 500 has a return of 2%? To answer this question, we calculate expected returns of a currency conditional on returns of the S&P 500. To do so, we need to model the relation between S&P 500 returns and carry trade returns. Let X_{SP} be the variable describing S&P 500 returns and x_{SP} are realizations of this variable. Similarly, X_{FX} is the variable of currency returns and x_{FX} are realizations of this variable. We first estimate a bi-variate Kernel density for realizations of currency returns and S&P 500 returns, $f(x_{FX}, x_{SP})$. The optimal bandwidth is chosen according to Botev, Grotowski, and Kroese (2010) applying their code.[21] Then, we calculate the expected currency return conditional on the realized S&P 500 return, $\mathbb{E}[X_{FX}|X_{SP}]$, which is given by

$$\mathbb{E}[X_{FX}|X_{SP} = x_{SP}] = \int x_{SP}\ f(x_{FX}|x_{SP}) \partial x_{FX} \tag{18}$$

This approach allows us to estimate conditional expectations while taking into account non-linear dependencies between the S&P 500 and currency returns.

C.2. Risk-neutral probabilities

For the US investor perspective we need risk-neutral probabilities derived from S&P 500 options. From the Wharton Research Data Service we retrieve end-of-month quotes on European S&P 500 index call options as well as the S&P 500 total return index level over the time period

[21] Using the rule-of-thumb which is optimal for normal distributions leads to a slightly lower bandwidth while the simple rule applied by Jackwerth (2000) leads to slightly higher values for the bandwidth. The results of our paper are not sensitive to the choice of bandwidth.

from January 2000 to June 2016. For each month, we have implied volatilities for a set of different strike prices. To be in line with the forward rates, we only select options with one month to maturity. Using the fast and stable method proposed by Jackwerth (2004), we inter- and extrapolate between the observed volatilities to fit an implied volatility curve across a fine grid of strike prices. The main advantage of this method is its simple computation as well as an external control of the trade-off between fit and smoothness. Then, we calculate the call option price for each implied volatility using the Black-Scholes option pricing formula and last, we use the result of Breeden and Litzenberger (1978) and approximate the state price density by the second derivative of the call price function with respect to the strike price. Moreover, we normalize these state prices to obtain risk-neutral probabilities which sum up to one. Note that this procedure is repeated every month such that we get a risk-neutral probability surface across strikes for every month.

C.3. Empirical results

In the following, we discuss the results of the crash-o-phobia asset pricing model from a US investor perspective. We again use non-linear least squares to estimate the parameters that minimize the squared difference between the option-implied and the model-implied risk-neutral density. Figure 8 shows the resulting fit for October 2008 and October 2012 for all ten currencies.

[Figure 8 about here.]

The fit of the model is very good. The black dashed line corresponds to the option-implied risk-neutral density calculated from S&P 500 options and the blue line represents the model-implied risk-neutral density calculated from the estimation of the Euler equation. The two lines overlap almost perfectly, which means that the explanatory power of the model is very good. Further, even in crisis times, the performance of the model does not deteriorate.

Panel A of Table VI shows the time-series average of each estimated parameter together with the corresponding standard error denoted in brackets.[22] We find that all parameter estimates are highly significant at the 1 % confidence level, where we test the parameters of the utility function (δ, κ) and lognormal distribution (μ, σ) against the null hypothesis of 0 while the parameters of the probability weighting function (γ, β^{-}, β^{+}) are tested against 1.

[22]Note that we again estimate the standard errors according to the Fama-MacBeth methodology.

The mean of the lognormal distribution characterizing the agent's beliefs, μ, is estimated to be 0.013 and the standard deviation is on average 0.0407. To describe the probability distortion, we use again Prelec (1998) two parameter specification given by equation (5). The value for γ is found to be 0.809, which is slightly higher than the values found for the currency investor but still in line with experiment and other empirical analyses. For β_+ and β_- our estimates are on average 0.830 and 0.834 respectively,[23] which is in line with experimental and empirical data, where values range between 0.7 and 1.2 (Gonzalez and Wu (1999), Fehr-Duda and Epper (2012), Polkovnichenko and Zhao (2013)). Overall, these values of γ and β mean that the representative US investor shows less probability weighting and smaller overweighting of very extreme events compared to the currency investor. For the loss aversion, we estimate an average value of 1.26. This is loss aversion is similar to the lowest values found for the currency investor.

In general, the evidence for crash-o-phobia is less pronounced for the US investor than for the currency investor. This is realistic since we assume that the US investor predominantly invests in US securities. Thus, any investment in currencies has presumably a diversification benefit, which is reflected in a lower loss aversion and a lower probability weighting. Still, there is evidence in favor of crash-o-phobia since γ is significantly smaller than one and δ significantly larger than zero.

The use of market data enables us to not only find parameter estimates at a single point in time, like in experiments, but to analyze as well in which states of the world crash-o-phobia strongly influences market perception. We thus investigate the time-series variation of the estimated parameters. These variations over time for the US investor perspective are illustrated in Figure 9 where the monthly estimates of each parameter are plotted in a separate graph. Overall, the plots show that crash-o-phobia is present in all time periods. It is however interesting to see that the extent to which the agent is crash-o-phobic increases in times of crises: for example, during the financial crisis of 2008 the distortion of probabilities (low γ, low β) is stronger and loss aversion is higher than during times without turmoil. Further, the parameter σ, indicating the beliefs about volatility, clearly increases during this period. Hence, the time-series variation of the parameters does, at least partially, reflect times of market turmoil.

[Figure 9 about here.]

[23] Our estimates for β_+ and β_- are very similar. This is in line with experimental results. In our case, the similarity can arise as well because we minimize the difference to a smooth function without kinks.

The increased crash-o-phobia during times of crises is reflected in Figures 3 and 8 as well: In contrast to the standard model, the crash-o-phobia model can explain the option-implied risk-neutral probability distributions very well. This is also due to varying degrees of crash-o-phobia which can match the time-variation in the risk-neutral probability distribution implied by the data. In Panel B of Table VI we additionally report parameter estimates for two points in time to further highlight the difference in parameter estimates between crises and non-crises periods. For October 2008, the loss aversion is estimated to be 1.69 while in October 2012 the loss aversion is only 1.04. In October 2008, γ is estimated to be 0.50, β_+ and β_- 0.44 implying that the probability distortion was very strong during the financial crisis. Four years later, in calmer times, the probability distortion is quasi absent (γ is 0.96 , β_+ and β_- are 1.01). Thus, the estimated level of crash-o-phobia is substantially higher in 2008 than in 2012, which enables the model to match time-varying option-implied distributions very well.

Crash-o-phobia is clearly of importance to explain currency carry trade returns even when we take the perspective of a US investor. Compared to the analysis of the currency investor perspective, the crash-o-phobia of the US investor is slightly muted; probably due to diversification effects.

V. Conclusion

In this paper we propose a new crash-o-phobia asset pricing model to price currency carry trade returns. We show that the standard asset pricing model with rational beliefs and CRRA utility fails to explain currency returns. Departing from this standard model, we relax assumptions on the belief formation and the utility function by allowing for crash-o-phobia, which entails belief estimation, belief distortion and loss aversion. We believe that the asymmetries in the return distribution of the carry trade, in particular negative skewness and tail risk, might well be captured by loss aversion and overweighting of rare events with small probabilities. We thus incorporate the crash-o-phobia elements into the Euler equation and use it to price a basket of 10 currency carry trade returns. Every month, we estimate a set of parameters by minimizing the squared difference between model-implied normalized state prices and option-implied risk-neutral densities via non-linear least squares. Our results suggest that carry trade investors exhibit substantial loss aversion and overweight states with low probabilities. While all our parameter estimates are in line with values found by experimental studies, it is important to note that all estimates are implied financial market data which further validates the crash-o-phobia asset pricing model.

To estimate the crash-o-phobia Euler equation, we need to define the state space. We assume that the currencies are priced by a currency investor whose state space is defined by the respective currency. The currency investor prices each currency separately which allows us to analyze not only time-series but also cross-sectional variation in parameter estimates: we show that investors pricing developed market currencies are more crash-o-phobic than investors holding emerging market currencies. This is consistent with higher returns of these currencies, i.e. not so crash-o-phobic investors hold the currencies which other investors deem too risky due to their crash-o-phobia. Less crash-o-phobic investors then earn a higher return. We show that crash-o-phobia matters to explain currency carry trade returns, both economically as well as statistically and even more so in times of crises. We further document that the estimated crash-o-phobia parameters are related to the higher moments of currency returns both in the cross-section and time-series. We find that lower probability weighting but higher loss aversion parameters are associated with more positive skewness and lower excess kurtosis of currency returns.

Finally, we show that the results of our crash-o-phobia asset pricing model are robust to changes in the assumption about the investor perspective. The results are still significant when we assume that all currencies are priced by the same representative US investor. Moreover, our results are consistent with experimental findings, which further supports their validity. The consistency with experimental studies as well as the statistical robustness of our results suggest that crash-o-phobia is a highly relevant factor for explaining currency carry trade returns. We believe that pursuing the approach of integrating behavioral aspects into asset pricing models improves our understanding of currency returns.

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A. Model Setup

The standard two-period asset pricing model with a representative investor follows closely the model outlined in Hens and Reichlin (2013) as well as the theory described in Hens and Rieger (2010). In our two-period model the representative investor trades a finite set of assets at time zero that deliver payoffs at period one in a finite set of states of the world. Markets are assumed to be complete.

- There are two time periods, $t = 0, 1$. In period $t = 0$, the state is denoted by $s = 0$. In period $t = 1$ a finite number of states $s = 1, \ldots, S$ can occur.
- There are K assets denoted by $k = 1, \ldots, K$. The payoff by asset k in state s is denoted by A_s^k and the asset price is denoted by $\mathbf{q} = (q^0, q^1, ..., q^K)$. Assuming no-arbitrage, asset prices can be expressed in terms of state price discounted asset payoffs, i.e. there exist state prices $(\pi_1, \pi_2, ...\pi_S) \in \mathbb{R}^S_{++}$ such that $q_k = \sum_{s=1}^S A_s^k \pi_s$ for $k = 0, \ldots, K$.
- The representative investor has exogenous wealth defined over all possible states $\mathbf{w} = (w_0, w_1, ..., w_S)'$ and a consumption stream $\mathbf{x} = (x_0, x_1, ..., x_S)$, where x_s are asset returns. He discounts future consumption at the rate β.

The agent maximizes expected utility over utility function u and expects state s to occur with probability p_s. The maximization problem can then be written as follows[24]

$$\max_{x_s} \quad u(x_0) + \beta \sum_{s=1}^S p_s u(x_s), \tag{19}$$

$$\text{such that} \quad x_0 + \sum_{s=1}^S \pi_s x_s = w_0 + \sum_{s=1}^S \pi_s w_s. \tag{20}$$

Formulating the Lagrangian

$$\mathbb{L} = u(x_0) + \beta \sum_{s=1}^S p_s u(x_s) - \lambda \left(x_0 + \sum_{s=1}^S \pi_s x_s - w_0 - \sum_{s=1}^S \pi_s w_s \right), \tag{21}$$

[24]Note that no-arbitrage implies that the maximization problem can be written in terms of returns and state prices.

which gives the following first-order conditions

$$\beta p_s u'(x_s) = \lambda \pi_s, \tag{22}$$

$$u'(x_0) = \lambda. \tag{23}$$

Inserting (23) into (22) results in the first-order condition in terms of state prices, π_s,

$$\frac{\beta p_s u'(x_s)}{u'(x_0)} = \pi_s \tag{24}$$

Because state prices are unobservable, we have to standardize to express the first-order condition in terms of risk-neutral probabilities, π_s^*,[25]

$$\frac{\frac{\beta p_s u'(x_s)}{u'(x_0)}}{\sum_s \frac{\beta p_s u'(x_s)}{u'(x_0)}} = \frac{\pi_s}{\sum_s \pi_s} \tag{25}$$

Since β and $u'(x_0)$ are constants, we can simplify

$$\frac{\frac{\beta p_s u'(x_s)}{u'(x_0)}}{\frac{\beta}{u'(x_0)} \sum_s p_s u'(x_s)} = \pi_s^* \tag{26}$$

and hence, the first-order condition is

$$\frac{p_s u'(x_s)}{\sum_s p_s u'(x_s)} = \pi_s^* \tag{27}$$

Thus, it is sufficient to know any utility function u and any consumption process x to determine the standardized state prices, also called the likelihood ratio process. Equally, knowing the risk-neutral probabilities and the physical probabilities is enough to back-out marginal utilities $u'(x_s)$.

[25]Using the result of Breeden and Litzenberger (1978), we can derive risk-neutral probabilities from call options prices.

Table I
Summary statistics

The table gives summary statistics for all 10 currency carry trade returns. It reports the mean, standard deviation and Sharpe Ratio, which are annualized and in percent, as well as the monthly skewness, kurtosis, minimum and maximum. The exact starting dates of currency returns are given in the column "start Returns" which are always 5 years prior to the first currency option-implied risk-neutral distribution specified in the last column "start RND". All data end in June 2016.

	Mean	Std Deviation	Sharpe Ratio	Skewness	Kurtosis	Min	Max	start Returns	start RND
CHF	2.03	10.90	0.19	0.12	4.49	-11.83	12.60	2000/04	2005/03
EUR	-0.43	10.26	-0.04	-0.15	3.84	-10.39	9.38	1999/02	2004/01
GBP	-0.50	8.77	-0.06	-0.47	4.57	-10.09	8.46	1998/11	2003/10
JPY	-1.54	10.03	-0.15	-0.05	3.25	-8.61	8.25	1998/11	2003/10
NOK	1.30	11.48	0.11	-0.30	3.71	-12.80	7.36	2000/04	2005/03
BRL	8.53	15.91	0.54	-0.59	4.42	-15.87	12.64	2004/04	2009/03
ZAR	10.14	19.49	0.52	0.44	4.14	-15.53	17.65	1998/11	2003/10
RUB	-0.23	15.24	-0.02	-0.66	6.62	-17.86	14.28	2004/04	2009/03
INR	2.03	7.61	0.27	-0.23	5.36	-7.45	7.81	2000/04	2005/03
MXN	0.67	9.94	0.07	-0.94	6.69	-13.90	7.40	2000/04	2005/03

Table II
Currency specific time-average parameter estimates

The table reports estimation results of the crash-o-phobia model from the perspective of a currency investor given by equations (9) and (10). Monthly parameter estimates are averaged over time and reported for each currency separately grouped by developed and emerging markets. Standard errors are denoted in brackets.

	μ	σ	γ	β^-	β^+	δ	κ	LA (30%)
Panel A: Developed market currencies								
CHF	-0.0282	0.0754	0.6039	1.7657	1.7636	1.8589	13.8325	2.8301
	(0.0044)	(0.0019)	(0.0137)	(0.0586)	(0.0567)	(0.0934)	(0.5480)	
EUR	-0.0381	0.0683	0.5447	1.9027	1.8875	1.6187	13.0306	2.5869
	(0.0045)	(0.0018)	(0.0110)	(0.0626)	(0.0612)	(0.0940)	(0.5317)	
GBP	-0.0391	0.0605	0.5205	1.9682	1.9008	1.5568	14.8498	2.5389
	(0.0041)	(0.0014)	(0.0098)	(0.0612)	(0.0580)	(0.0988)	(0.7364)	
YEN	-0.0425	0.0981	0.7124	2.0575	2.1055	2.6281	14.0351	3.5897
	(0.0079)	(0.0039)	(0.0151)	(0.0892)	(0.0887)	(0.0798)	(0.5432)	
NOK	-0.0581	0.0730	0.4469	1.8160	1.8210	0.9982	13.7762	1.9825
	(0.0050)	(0.0019)	(0.0098)	(0.0518)	(0.0504)	(0.0597)	(0.5828)	
Panel B: Emerging market currencies								
BRL	-0.0636	0.0725	0.3812	1.9162	1.7705	0.7009	14.5268	1.6920
	(0.0069)	(0.0026)	(0.0113)	(0.0756)	(0.0728)	(0.1492)	(0.7581)	
ZAR	-0.1464	0.0737	0.2518	2.1585	2.2061	0.2895	20.7925	1.2889
	(0.0054)	(0.0013)	(0.0069)	(0.0529)	(0.0567)	(0.0173)	(0.8113)	
RUB	-0.1072	0.0803	0.3945	2.6595	2.5668	0.4567	19.5174	1.4554
	(0.0086)	(0.0052)	(0.0149)	(0.1224)	(0.1204)	(0.0702)	(1.8989)	
INR	-0.0514	0.0527	0.4591	2.4444	2.1986	1.7263	13.1342	2.6934
	(0.0036)	(0.0016)	(0.0116)	(0.0812)	(0.0846)	(0.1427)	(0.9032)	
MXN	-0.0890	0.0612	0.3750	2.4094	2.2689	0.7653	17.4462	1.7612
	(0.0052)	(0.0021)	(0.0104)	(0.0746)	(0.0764)	(0.1022)	(1.1245)	

Table III
Model comparison

The table reports comparisons between the crash-o-phobia model, the CRRA benchmark model (CRRA), a CRRA model with belief estimation (CRRA.mis), and a model with CRRA utility, belief estimation and probability distortion (CRRA.dismis). For each currency, the first row reports the absolute level of the information criterion for each model averaged across time (average AIC). The second line compares the number of months the crash-o-phobia model outperforms the respective benchmark model in terms of lower AIC. The third line shows a Kolmogorv-Smirnov test, where we test for equality of distributions between the option-implied risk-neutral density and the model-implied density at a 5 % confidence level. The number gives the percentage of months, where the test for equality has been rejected.

Currency	Statistic	CRRA	CRRA.mis	CRRA.dismis	Crash-o-phobia
Panel A: Developed market currencies					
CHF	average AIC	-13689.12	-17873.35	-18157.56	-19347.61
	$AIC_{crash} < AIC_{model}$	100.00	93.38	92.65	
	KS test: H_0 rejections	100.00	6.62	2.94	0.00
EUR	average AIC	-13697.55	-17689.47	-18115.60	-18967.37
	$AIC_{crash} < AIC_{model}$	100.00	90.67	81.33	
	KS test: H_0 rejections	99.33	10.67	0.00	1.33
GBP	average AIC	-13677.69	-17382.52	-17743.41	-18735.17
	$AIC_{crash} < AIC_{model}$	100.00	96.08	90.20	
	KS test: H_0 rejections	98.69	14.38	1.31	1.31
YEN	average AIC	-13587.36	-17541.00	-17541.69	-18924.24
	$AIC_{crash} < AIC_{model}$	100.00	89.54	83.66	
	KS test: H_0 rejections	100.00	15.03	33.33	4.58
NOK	average AIC	-13562.31	-17790.67	-18524.38	-19170.04
	$AIC_{crash} < AIC_{model}$	100.00	86.76	77.94	
	KS test: H_0 rejections	100.00	22.06	0.74	0.00
Panel B: Emerging market currencies					
BRL	average AIC	-13771.40	-17167.92	-17841.15	-18179.11
	$AIC_{crash} < AIC_{model}$	100.00	94.32	79.55	
	KS test: H_0 rejections	98.86	56.82	22.73	18.18
ZAR	average AIC	-13958.81	-16889.23	-17774.85	-18460.38
	$AIC_{crash} < AIC_{model}$	100.00	100.00	87.58	
	KS test: H_0 rejections	100.00	89.54	19.61	18.95
RUB	average AIC	-13601.67	-16983.15	-17152.67	-17583.58
	$AIC_{crash} < AIC_{model}$	100.00	93.18	84.09	
	KS test: H_0 rejections	100.00	77.27	40.91	44.32
INR	average AIC	-13223.46	-16809.71	-17112.21	-17443.28
	$AIC_{crash} < AIC_{model}$	99.26	86.03	83.09	
	KS test: H_0 rejections	99.26	53.68	19.12	20.59
MXN	average AIC	-13581.11	-16643.33	-17058.20	-17670.21
	$AIC_{crash} < AIC_{model}$	100.00	97.06	88.24	
	KS test: H_0 rejections	100.00	86.76	25.00	24.26

Table IV
Explaining higher moments of currency returns

The table reports regression results for explaining the skewness and excess kurtosis of currency returns by the estimated crash-o-phobia model parameters, in particular the probability weighting parameter γ and β^- as well as the level of loss aversion at 30 %. The first part shows the results of the time-series regressions given by equations (12) and (13), while the second part summarizes the cross-sectional regression results according to equations (14) and (15). The skewness and excess kurtosis of currency returns are estimated over a rolling window of 5 years. Estimates of the constant terms are not tabulated. Standard errors are denoted in brackets, where * and ** indicate significance at the 10 % or 5 % levels, respectively. For the time-series regressions, we report Newey and West (1987) standard errors with 59 lags and cross-sectional standard errors are calculated according to the sample averages of rolling Fama and MacBeth (1973) regressions.

Time-series

	Skewness				Excess Kurtosis			
Currency	γ	β^-	LA (30%)	R^2_{adj}	γ	β^-	LA (30%)	R^2_{adj}
Panel A: Developed market currencies								
CHF	1.27**	0.07	-0.03	11.38	-2.84**	-0.61**	-0.22	15.90
	(0.50)	(0.10)	(0.06)		(1.18)	(0.25)	(0.24)	
EUR	0.45**	0.03	0.11**	16.71	-0.22	-0.11	-0.22*	4.66
	(0.19)	(0.04)	(0.04)		(0.53)	(0.10)	(0.13)	
GBP	0.33	0.11**	0.15**	26.88	-1.28	-0.33**	-0.49**	20.36
	(0.28)	(0.05)	(0.03)		(1.18)	(0.15)	(0.15)	
YEN	1.06**	0.04**	-0.04	36.77	-0.93**	0.02	0.02	14.02
	(0.19)	(0.01)	(0.03)		(0.28)	(0.05)	(0.04)	
NOK	0.35	0.21*	0.16*	11.44	-0.48	-0.67**	-0.42	14.18
	(0.33)	(0.11)	(0.09)		(0.78)	(0.23)	(0.28)	
Panel B: Emerging market currencies								
BRL	-1.34**	-0.11**	0.06**	13.30	2.82**	0.29**	-0.10*	11.56
	(0.42)	(0.05)	(0.02)		(0.86)	(0.08)	(0.06)	
ZAR	-0.65	-0.24**	-0.37	11.85	0.53	0.38**	0.54	9.65
	(0.57)	(0.08)	(0.24)		(1.05)	(0.13)	(0.35)	
RUB	0.13**	-0.01	0.07	-0.54	-2.00	0.40**	-0.37**	19.86
	(0.03)	(0.04)	(0.05)		(1.23)	(0.07)	(0.14)	
INR	0.07	0.01	0.04**	3.59	-0.56	-0.03	0.26**	19.05
	(0.15)	(0.03)	(0.02)		(0.51)	(0.06)	(0.10)	
MXN	2.18**	-0.03	0.16**	29.09	-9.19**	0.33**	-0.65**	25.19
	(0.72)	(0.04)	(0.04)		(3.62)	(0.15)	(0.15)	

Cross-section

	Skewness			Excess Kurtosis		
	γ	β^-	LA (30%)	γ	β^-	LA (30%)
	1.19**	0.07**	0.08**	-2.19**	-0.15*	-0.56**
	(0.16)	(0.03)	(0.03)	(0.50)	(0.09)	(0.12)

Table V
Currency strategies

The table reports summary statistics of four currency strategies. The carry strategy sorts according to the interest differential, the momentum strategy sorts on past returns, the probability weighting strategy sorts on the estimated probability weighting parameter γ and the loss aversion strategy sorts on the estimated level of loss aversion. The mean and volatility are annualized. The time period is March 2005 to June 2016.

Strategy	Mean return (%)	Volatility (%)	Skewness	Excess Kurtosis	Sharpe Ratio
Carry	2.51	8.03	-0.23	-0.08	0.31
Momentum	2.11	6.68	-0.08	0.55	0.32
Loss Aversion	2.62	6.83	-0.27	0.58	0.38
Probability Weighting	-0.44	6.11	0.61	2.03	-0.07

Table VI
US investor perspective time-average parameter estimates

The table reports estimation results of the crash-o-phobia model from the perspective of a US investor. Panel A gives monthly parameter estimates, which are averaged over time and standard errors are denoted in brackets. Panel B reports parameter estimates for October 2008 and October 2012. The non-linear least square standard errors are given in brackets for these two dates.

	μ	σ	γ	β^{-}	β^{+}	δ	κ	LA (30%)
Panel A: Average over time								
	0.0130	0.0407	0.8094	0.8290	0.8339	0.2704	57.0679	1.2579
	(0.0023)	(0.0015)	(0.0136)	(0.0298)	(0.0294)	(0.0340)	(7.2238)	(0.0341)
Panel B: Selected months								
October	0.0431	0.0199	0.5011	0.4442	0.4446	0.8433	4.8948	1.6855
2008	(0.0006)	(0.0001)	(0.0074)	(0.0055)	(0.0084)	(0.4869)	(0.0000)	(0.4869)
October	0.0035	0.0403	0.9598	1.0094	1.0077	0.0481	4.4200	1.0380
2012	(0.0002)	(0.0000)	(0.0012)	(0.0054)	(0.0053)	(0.0084)	(0.0000)	(0.0084)

Figure 1. Utility function with loss aversion

The figure shows a linear utility function and loss averse utility function proposed by Rosenblatt-Wisch (2008) with a κ of 20 and a δ of 0.5.

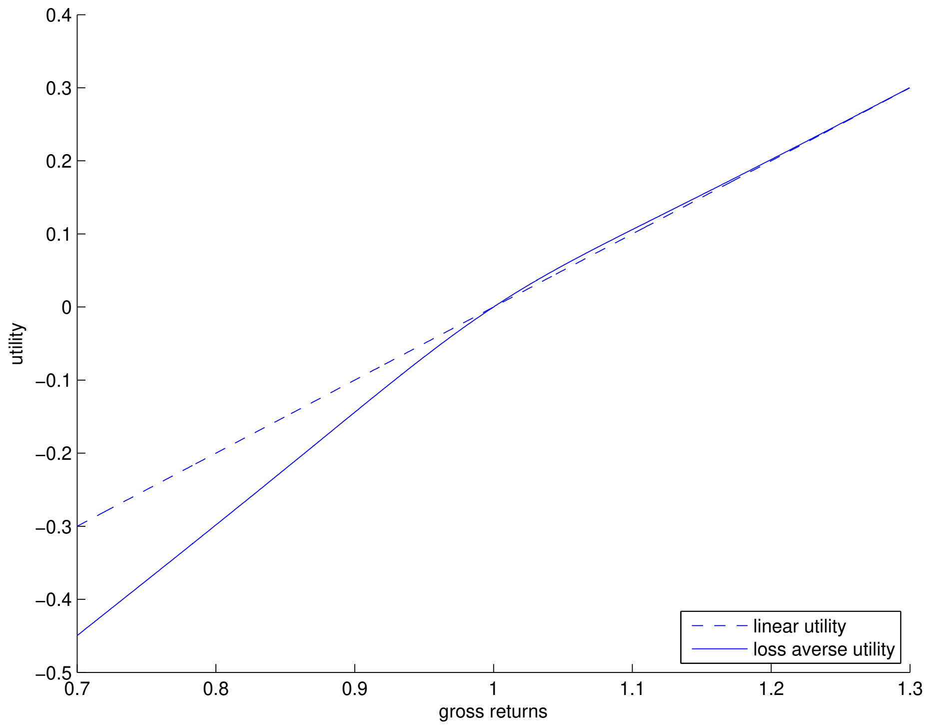


Figure 2. Probability weighting function

The figure shows the two parameter probability weighting function proposed by Prelec (1998) with a γ of 0.5 and a β of 0.8.

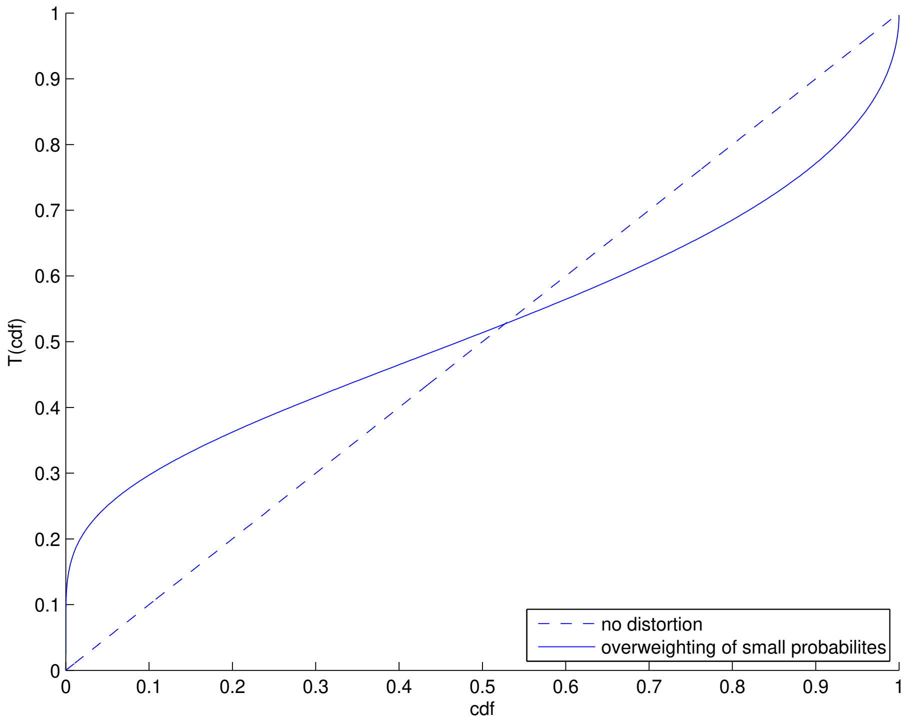
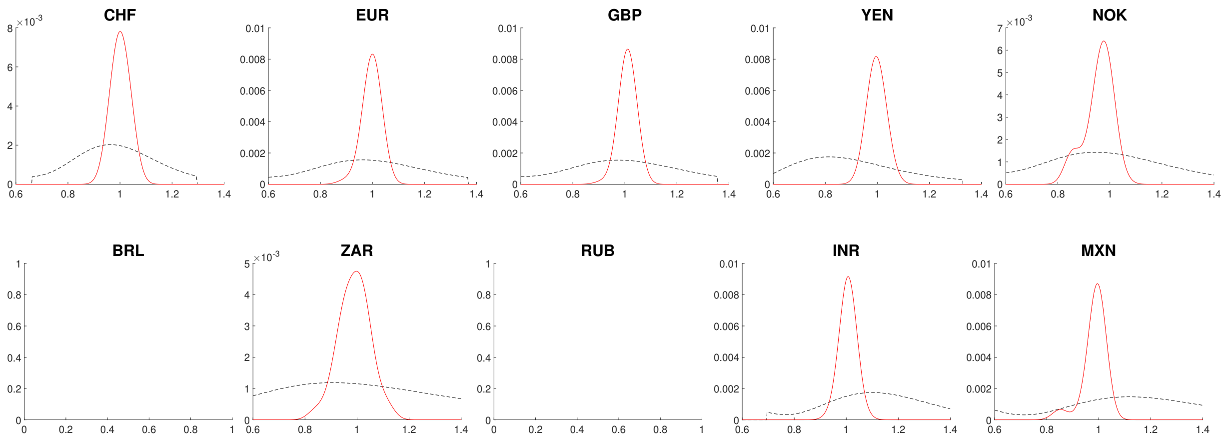


Figure 3. Risk-neutral densities: standard model with rational beliefs

The figure shows the risk-neutral probability distribution implied by the CRRA model (1) (red line) for each currency together with the option-implied risk-neutral density (black dotted line) for October 2008 and October 2012.

October 2008



October 2012

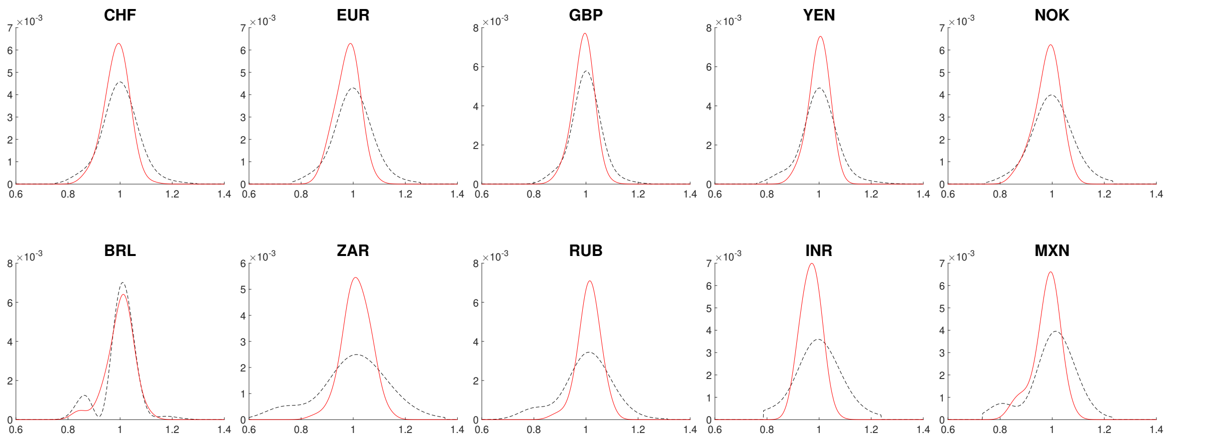
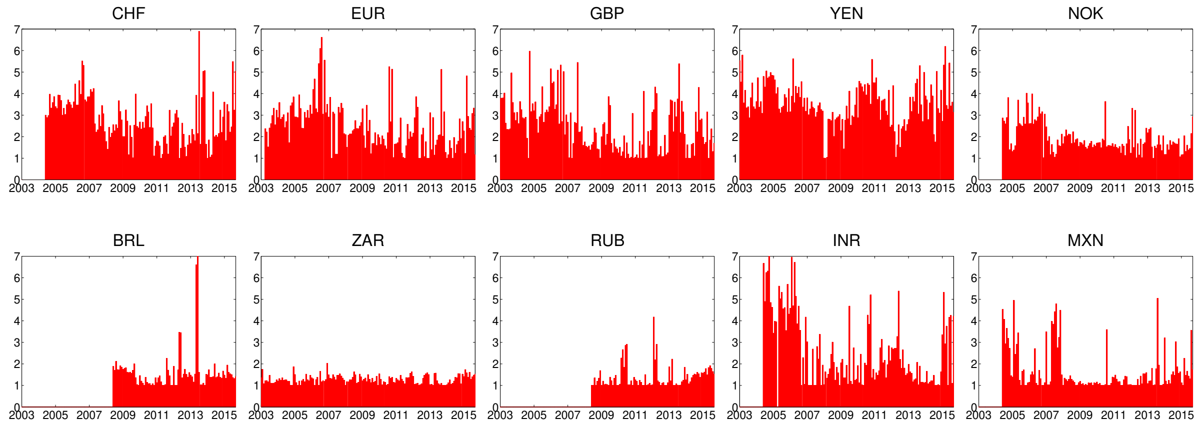


Figure 4. Currency specific crash-o-phobia estimates

The figure shows the currency specific monthly parameter estimates for the loss aversion evaluated at 30 % and the probability weighting parameter γ for the crash-o-phobia model from the currency investor perspective.

Loss aversion (at 30%)



Probability weighting (gamma)

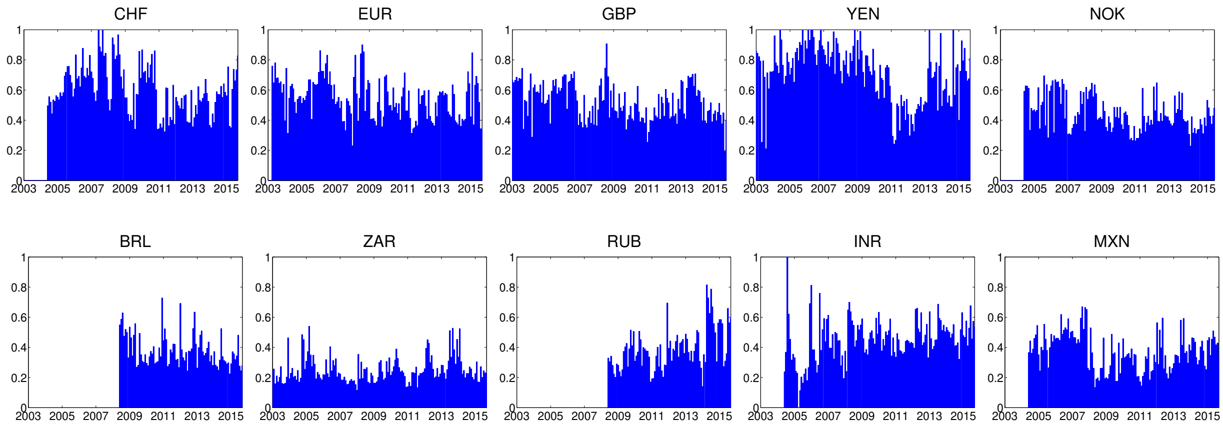


Figure 5. Currency specific beliefs

The figure shows the currency specific monthly parameter estimates for the beliefs following a lognormal distribution with parameters μ and σ. The estimates are from the crash-o-phobia model and currency investor perspective.

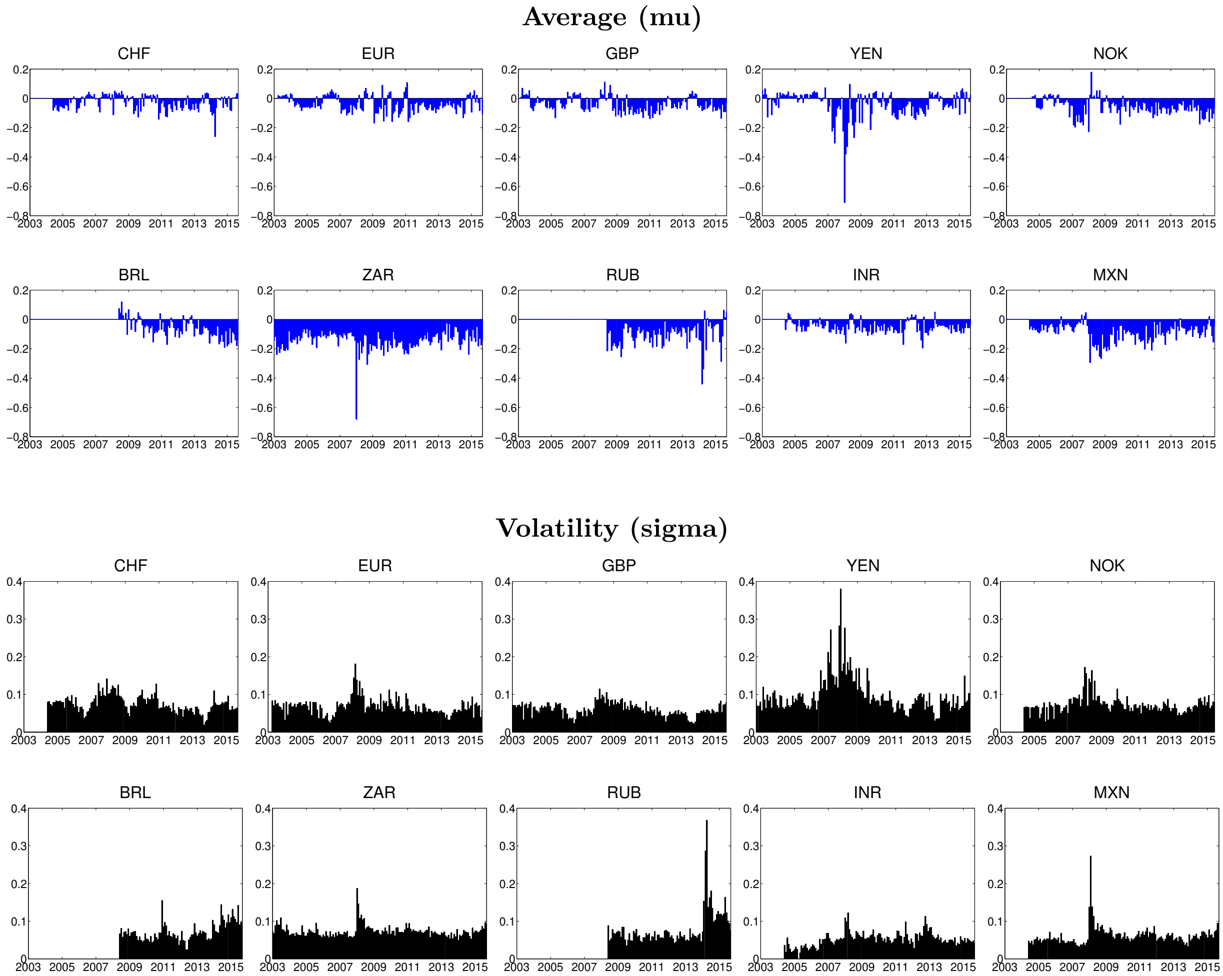
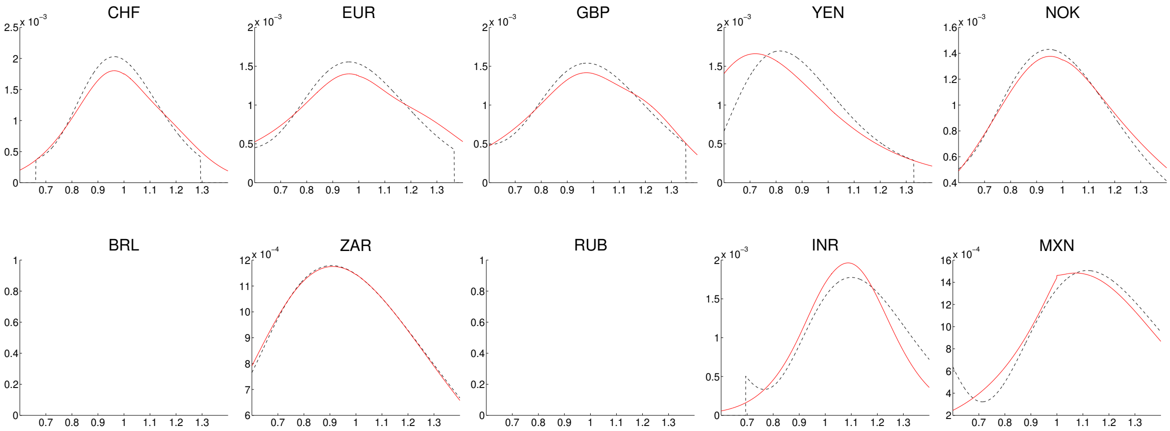


Figure 6. Risk-neutral densities: crash-o-phobia model (currency investor)

The figure shows the risk-neutral probability distribution implied by the crash-o-phobia model (9) (red line) for each currency together with the option-implied risk-neutral density (black dotted line) for October 2008 and October 2012.

October 2008



October 2012

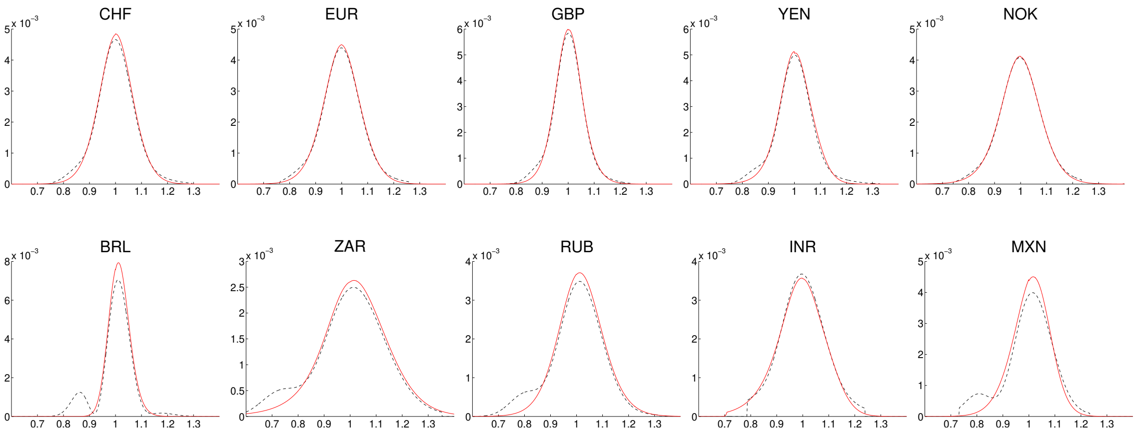


Figure 7. Cumulative returns of currency strategies

The figure shows the cumulative returns of four currency strategies. The carry strategy invests in currencies with high interest rate differentials towards the dollar. The momentum strategy invests in currencies, which performed well during the last month. The loss aversion portfolio invests in currencies for which we estimated a low loss aversion coefficient in the last month whereas the probability weighting portfolio invests in currencies for which estimated a high γ. All portfolios are long-short portfolios. Trading costs are not considered. The time period is March 2005 to June 2016.

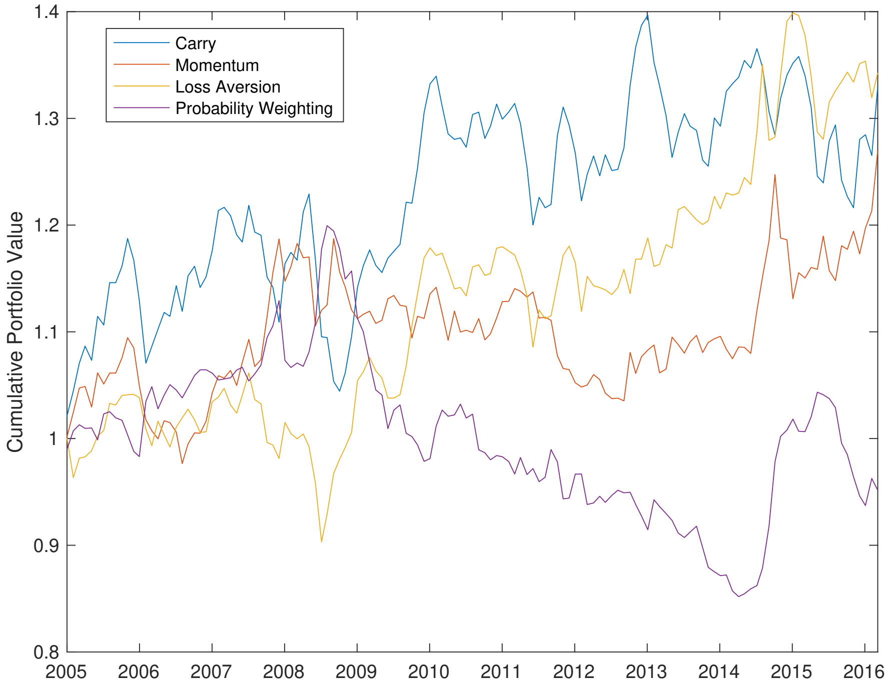
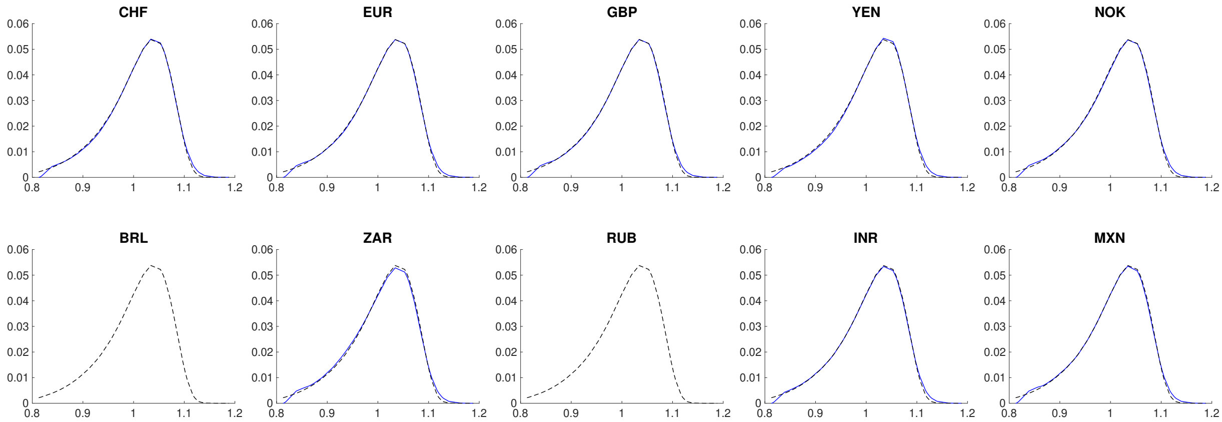


Figure 8. Risk-neutral densities: crash-o-phobia model (US investor)

The figure shows the S&P 500 option-implied risk-neutral densities (black dashed line) together with model-implied risk-neutral densities using the crash-o-phobia model from the US investor perspective (blue line) for October 2008 and October 2012.

October 2008



October 2012

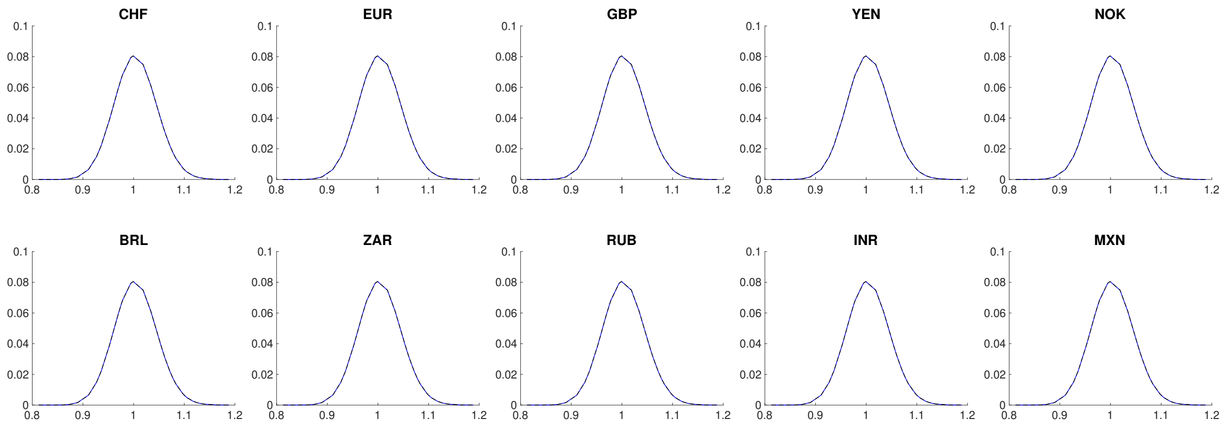
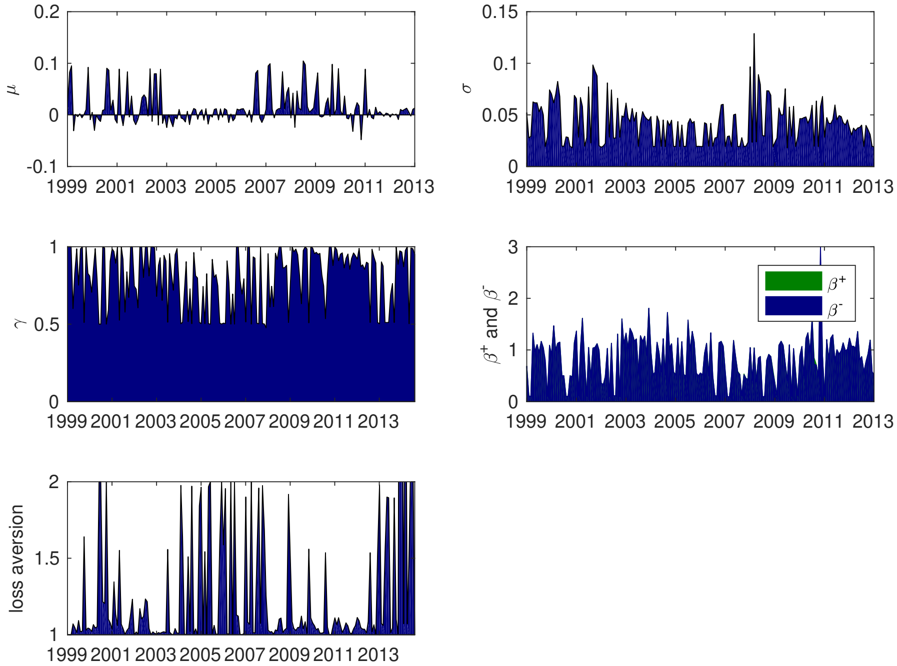


Figure 9. US investor perspective parameter estimates over time

The figure shows the monthly parameter estimates of the crash-o-phobia model from the US investor perspective.



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